The Dissertation Committee for Bryan Michael Stephens certifies that this is the approved version of the following dissertation:

Entrepreneur Career Paths, Location Choice, and Ecosystems: An Empirical Analysis

Committee:

John Sibley Butler, Supervisor

Rajiv Garg

Wenhong Chen

Pamela Paxton

Entrepreneur Career Paths, Location Choice, and Ecosystems: An Empirical Analysis

by

Bryan Michael Stephens

Dissertation

Presented to the Faculty of the Graduate School of

The University of Texas at Austin

in Partial Fulfillment

of the Requirements

for the Degree of

Doctor of Philosophy

The University of Texas at Austin

May 2018

Dedication

Dedicated to my parents, David and Deanna, and my sister, Brittany, for their unwavering and unconditional love and support.

Acknowledgements

First, my deepest gratitude to my advisor and mentor John Sibley Butler. I am forever grateful for his generosity, wisdom, and support. Also my deepest thanks to my other advisors, Rajiv Garg, Wenhong Chen, and Pamela Paxton, for their dedication, encouragement, guidance, and invaluable insights.

Thanks to the faculty and staff in the Department of Sociology for their help and support. A special thanks to Shelley Nelson, a mentor and friend who made enduring investments in my future. I also want to thank many who were critical to my intellectual development including Dan Powers, Ari Adut, Caroline Bartel, James K. Galbraith, Y. Sekou Bermiss, David Harrison, Chandler Stolp, Joshua Busby, Rajesh Chandy, Jane Rogan, Aurelian Craiutu, and Carolyn Goerner.

Sincere thanks to Ben Barnes, Gregory Pogue, the IC^2 Institute, and the Herb Kelleher Center for Entrepreneurship for the generous investment and support. I also want to think my fellow graduate students and friends for their feedback and positive encouragement throughout this process. In particular, I want to thank Haris Krijestorac, Parshu Hotkar, and Jonathan Chen. Also, a special thanks to Roxanne Garza.

Most importantly, none of this is possible without the unconditional love and support I receive from my parents, David and Deanna, and my sister, Brittany. Thanks for always being there to lift me up, make me smile, and give me the confidence to face any challenge.

Entrepreneur Career Paths, Location Choice, and Ecosystems: An Empirical Analysis

Bryan Michael Stephens, Ph.D.

The University of Texas at Austin, 2018

Supervisor: John Sibley Butler

Abstract: This dissertation consists of three research articles investigating three related research questions about entrepreneurial ecosystems and the career and location transitions of technology entrepreneurs. Altogether, the analyses improve our understanding of how particular work experiences and skills can shape the career paths of entrepreneurs and executives and how certain locations are consistently better at retaining/attracting entrepreneurial talent. The first article explores the common career paths of entrepreneurs, executives, and senior managers in the high-tech industry. I build career trajectories (as network graphs) that provide insights on career paths of entrepreneurs, executives, and senior managers based on a large dataset of work histories. Focusing on the high-tech industry, I find that individuals with certain transferable skills—notably technical, management, mixed, and boundary-spanning experience—are more likely to be in position to capitalize on job opportunities across industries. Furthermore, I test these insights by developing and refining a supervised learning model for predicting individual career transitions. In the second article, I investigate why certain U.S. metropolitan areas are better able to retain and attract technology entrepreneurs. Placing the entrepreneur at the center of the analysis, I examine the role of regional economic factors, regional funding opportunities, and personal social networks on

entrepreneur decisions to start a high-tech firm in a specific location. The third article investigates the entrepreneurial ecosystems of Silicon Valley, Austin, Boston, and New York, which are well-established innovation-centered business clusters and entrepreneurial “talent magnets”. Following a brief overview and history of the entrepreneurial ecosystems of each region, I specify models (for each region) testing the importance of social network ties, funding, education, and cumulative work experience in driving the entrepreneurs’ location choice decisions. I supplement the empirical findings by analyzing interview data collected from technology entrepreneurs to explain how particular structures within entrepreneurial ecosystems facilitate interaction and networking among entrepreneurs—offering potential explanations for some of the observed variation between regions.

Table of Contents

List of Tables

List of Figures

Chapter 1: "Which Way I Ought to Go?" Career Trajectories of Entrepreneurs, Executives, and Senior Managers in High-Tech

This paper analyzes 67,000 career profiles from a popular social networking platform. I build career trajectories (as network graphs) that provide insights on career paths of entrepreneurs, executives, and senior managers. In these career trajectory graphs, each node is a job consisting of an industry-level and seniority-level classification. Focusing on high-tech industry, I find that individuals with certain transferable skills — notably technical, management, mixed, and boundary-spanning experience — are more likely to be in position to capitalize on job opportunities across industries. Furthermore, I test these insights by developing and refining a supervised learning model for predicting individual career transitions of 10,000 individuals and achieve 48% accuracy for 204 job choices. Managerially, these insights can help in recruitment, career planning, job search and more.

INTRODUCTION

> "Would you tell me, please, which way I ought to go from here?"
> "That depends a good deal on where you want to get to."
> "I don't much care where –"
> "Then it doesn't matter which way you go."
> ― Lewis Carroll, Alice in Wonderland

Feelings of career uncertainty are well-documented by many recent college graduates and current workers in the labor force. In a recent survey of working U.S. adults, 58% of all respondents, and 73% of working professions in their 30s, expressed interest in changing careers (McLaughlin 2015). Some of the top reasons given for this interest include feeling "burned out" or the loss of passion in their current field, not making enough money, and the lack of opportunity for advancement in their current field. This should be a major concern among managers because this suggests a mismatch between the occupational career goals and ambitions of employees and the job responsibilities they currently occupy. This mismatch fosters worker dissatisfaction, which is associated with lower productivity and higher turnover (Lee, Carswell and Allen 2000).

Most professionals would benefit from advice in identifying the career choices to achieve a specific career goal. Almost every professional is asked about his/her five (or ten) year plan during interviews and over the course of their corporate tenure. This is an extremely complex and difficult question for young professionals, who lack information on how their prospective experiences will shape future career opportunities. Thus, a more complete understanding of career dynamics based on career transitions is important from different perspectives. It can help job seekers identify career transitions within a five (ten) year window that are positively associated with desirable career goals. It can help employers identify candidates that are likely to have the skills for the next job and potentially reduce costly job turnover. It can help policymakers better understand shifts in the labor market and develop policies to encourage better alignment of skills and industry needs in the workplace.

Currently, we lack the tools that connect career goals and outcomes with the discrete career steps that increase the likelihood of achieving those outcomes. From the workers' perspective, it would be helpful to know the most common career paths taken by those executives, entrepreneurs, and senior managers, so they can align their work experiences and skills with the job outcomes they wish to achieve. For those that have lost passion or feel they cannot advance further in their current field, it would helpful to know what career steps they should take to reach new career goals in other fields, without starting over at the bottom of the career ladder. Current employees are unlikely to share newly developed career goals in other fields with human resources or other personnel inside the organization, because it could adversely impact personal relations or treatment in the near term—before the individual is ready to make the career transition.

Career counseling or "coaching" is the main resource available to individuals seeking advancement towards career goals. Career coaching involves an assessment of a person's strengths and weakness, job preferences, values, interests, and personal life concerns, and then evaluating compatible work opportunities both within and outside the current organization (Feldman 2001). While there are studies that establish the plausible benefits of career coaching on worker satisfaction and performance, there are also many weaknesses and potential downsides. For example, many career coaches rely on imperfect coaching heuristics that are subject to individual biases based on their stock of experiences with clients. Also, many coaches use a battery psychometric tools (e.g., Myers-Briggs Type Indicator) (Kennedy and Kennedy 2004), which are problematic when used as the primary basis for making recommendations on career choices (Tieger, Barron and Tieger 2014). These psychometric assessments can oversimplify a person's compatibility with a career choice and create biased preconceptions and entrench idiosyncratic judgments the coach or client makes about his/her abilities and preferences regarding career choices (Rynes, Giluk and Brown 2007). Furthermore, career coaches do not have tools that directly address questions regarding the various paths an individual can take to reach career outcomes or goals. To improve career management, there have been calls for analysis of longitudinal data on individuals' job- and industry-switching histories to improve our understanding of associations and mechanisms underlying career transitions (Kim et al. 2014).

Many scholars have focused on identifying patterns in workers transitions into and within the labor market (Fallick, Fleischman and Rebitzer 2006, Joseph et al. 2012, Scherer 2001). The structure and mechanisms of job transitions is closely associated with intergenerational social mobility and inequality (Blau and Duncan 1967, Rosenfeld 1992). As prior work documents, the economic environment and market forces have eroded the traditional conception of organizational careers, where individuals follow relatively discrete, linear transitions within one or two organizations (Bidwell and Briscoe 2010, Rosenbaum 1979). The rise of novel career paths lead to notion of "boundaryless" careers, where worker careers bounce around between multiple positions within multiple organizations (DeFillippi and Arthur 1996, Greenhaus, Callanan and DiRenzo 2008, Joseph et al. 2012).

This broader variance among career trajectories, combined with the proliferation of job titles, roles, and responsibilities makes pattern detection among job transition sequences notoriously difficult (Abbott and Hrycak 1990). Mimno and McCallum (2008) propose a topical sequence model of career path trajectories based on latent topics detected in the components of job descriptions on resumes. I build on this earlier research by investigating a large volume of digital user-reported career profiles available on social networking platforms. I utilize network methods for visualizing and finding patterns in aggregated career trajectories and refine a supervised learning method to increase prediction accuracy for subsequent career transitions.

Big data introduces a new resource for identifying particular career paths associated with particular career outcomes. Identifying these career paths is really an empirical question. That is, individuals that reach particular career outcomes (e.g. CEOs, senior managers, entrepreneurs) transitioned from a sequence of prior work experiences. We know these paths exist because we have the aggregate data that shows what job transitions people have made over their career. These lead to the core research question: what career transition insights can we observe from big data? Moreover, as a way of empirically testing these observed insights, can we use those transition patterns to predict individual career outcomes?

Data constraints have prevented research from finding patterns and drawing generalizable insights based on individual work histories. Finding insights from work histories requires a large volume of individual careers, because small samples will suffer from selection bias, which weakens the generalizability of the insights. Individual work history data is very difficult and costly of obtain via traditional survey collection. However, a significant portion of the labor force now reports individual career histories on work-related social networking platforms (e.g., LinkedIn, XING, Viadeo). Career profiles on social networking platforms provide both the scale and granular job transition details to investigate patterns in occupational mobility of careers like entrepreneurs, executives, and senior managers. Even with career data available on individual profiles, large scale collection of individual public profiles is extremely difficult. To my knowledge, this is the first study to use big data from a career networking platform for career transition insights and large scale predictive analysis of individual career paths.

This paper has two main objectives. First, I analyze a large volume of data, available in the form of online career profiles on a social networking platform, to find and explain common patterns in career trajectories for entrepreneurs, executives, and persons in senior-level roles within firms. Second, I test the observed insights by developing a model for predicting career choices of individuals. I build career trajectories of individuals as a network graph where each node is a job consisting of an industry-level and seniority-level classification. I combine the graphs for each individual to build an aggregate career transition matrix for each of the preferred career outcomes (entrepreneur, executive, senior management, senior technical staff). I then develop and refine supervised learning method to increase prediction accuracy. In this study, I focus entirely on the insights from career transition networks for people who listed their last career in high-tech entrepreneurship, executive, or a senior management/technical role.

BACKGROUND LITERATURE AND THEORY

Many scholars in the social sciences have studied work, occupations, and individual careers. Early studies often focused on career paths within particular occupations (Becker 1952, Hall 1948) and organizational careers (Vroom and Maccrimmon 1968), emphasizing the relatively linear progressions among professional careers. Later, scholars recognized that a significant portion of individual careers were highly disordered, even among professional occupations (Evans and Laumann 1983). Shifting focus, many studies explored occupational mobility and the relation between inter-organizational or inter-occupational career transitions and changes in social status (prestige) (Kalleberg and Hudis 1979). White (1970) demonstrated the link between individual careers and organizational structure, inspiring a range of formal models of organizational mobility (Rosenbaum 1979, Stewman and Konda 1983). Recognizing the complex sequencing of most individual careers, most studies in the career literature did not consider the influence of prior sequencing of jobs in an individual's work history on the future career transitions or career outcomes (Leung 2014).

Opportunity structures and skill transferability

Opportunity structures in the labor market is a key factor that drives people to switch from one industry to another. In the last few decades, certain industries have experienced more job growth than others. Figure 1 shows the indexed employment growth for various industries in the United States. Since 2000, education and health services have maintained the largest employment growth of any industry and they are the only industries to continue to grow through the 2008 recession caused by the financial crisis. Other industries with strong growth since 2000 include computer and mathematical occupations, leisure and hospitality (e.g., arts, media, entertainment, recreation), and professional and business services. There has been slight employment growth in the finance and legal services and negative growth in information services, at least in part due to expanding scope of automation (Brynjolfsson and McAfee 2011). In a stylized labor market, individual career transitions are in part shaped by this variation in industry growth as individuals seek out job opportunities that offer better compensation and prospects for further advancement as they gain experience. The faster growing industries providing more attractive career opportunities, while lower growth industries offer more competition among labor and fewer career opportunities.

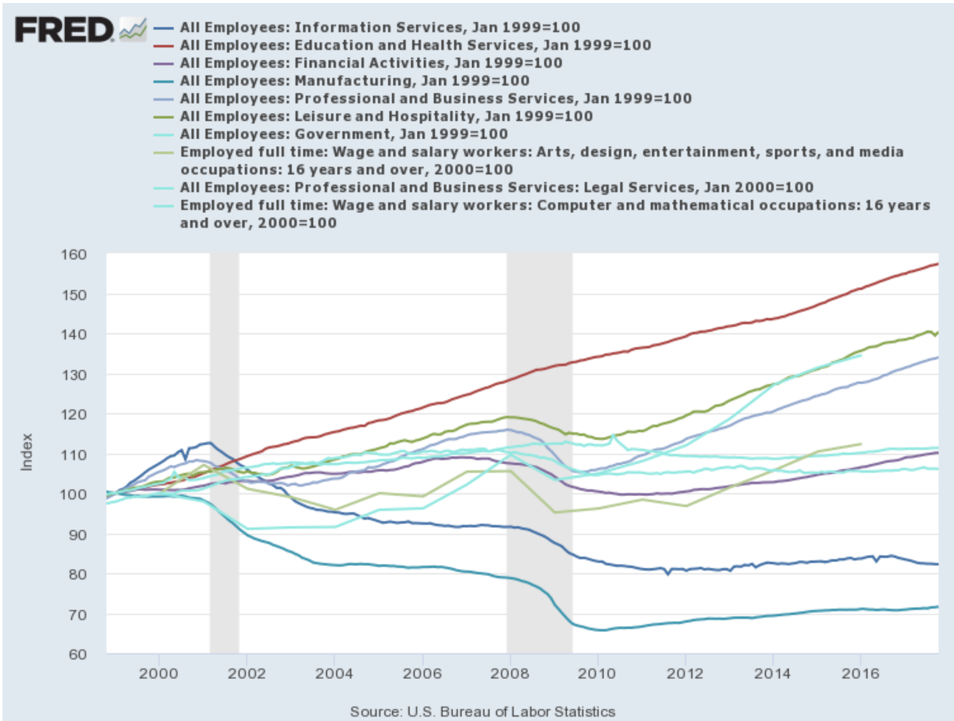


Figure 1: Indexed Employment Growth by Industry (1999-2017) (Index=1999)

In addition to the career opportunities enabled by structural changes in the labor market, individual career choices are shaped by the transferability of their skills and knowledge acquired through education and work experience (Bidwell and Briscoe 2010). Many studies have examined isolated career transitions, particularly related to job turnover within an organization. For example, past literature has shown high rates of turnover among IT jobs (Tambe and Hitt 2013) and identified several factors influencing this turnover including job satisfaction, organizational commitment, human capital, intrinsic motivation, external labor market conditions, boundary-spanning activities, and low promotability (Joseph et al. 2007).

Recently, MacCrory, Choudhary and Pinsonneault (2016) focused on boundary-spanning roles and infrequent intra-firm promotability as key factors for IT professionals frequently switching jobs, suggesting firms can reduce turnover by offering frequent and small promotion ladders. Boundary-spanning activities are a key factor explaining frequent job transitions because activities in these roles require a broader skillset, including the knowledge, technical abilities, and domain-specific language associated with different departments (fields) (Joseph et al. 2012).

Since these boundary-spanning duties are critical to the firm, these roles have some degree of power (Baroudi and Igbaria 1994) but can also be highly stressful (Kahn et al. 1964) and, in turn, promote turnover. Thus, persons in boundary-spanning roles have more transferable skills that are valued by many departments and organizations, including those in different industries. This insight has fueled the notion of "boundaryless" careers, in which workers with transferable skills jump around between multiple positions within multiple organizations (DeFillippi and Arthur 1996, Greenhaus, Callanan and DiRenzo 2008, Joseph et al. 2012). Workers develop portable identities around their repertoire of skills and abilities, which they can deploy over time across a wide range of organizations and job responsibilities (Petriglieri, Petriglieri and Wood 2017).

While other types of jobs may also perform boundary-spanning activities, many IT and other technical/analytical roles are associated with this kind of boundary-spanning work. Technical skills such as computer programming, database management, and data analytics are highly transferable in the modern information economy. Firm demand for individuals with technical skills has steadily increased (Campbell et al. 2012, Ganco, Ziedonis and Agarwal 2015). For example, based on data from the online job search website Indeed.com, since 2013, the portion of U.S. jobs requiring skills involving artificial intelligence as increased by a factor of 4.5 (aiindex.org). Thus, when considering entire sequences of career trajectories, one would expect to see technical staff transitioning to different industries, capitalizing on their transferable skillset.

The benefits of a broader, more generalized skillset may apply to areas other than technical or STEM (Science, Technology, Engineering, and Mathematics) related skills and fields. While majors from STEM fields yield predictably higher lifetime earning potential relative to majors in the humanities and liberal arts, there are large variations in earning potential both within and between majors. Among individuals with more ability in the upper quarter of the lifetime earning distribution, the earnings of some broader, non-STEM degrees (e.g., economics, political science) are actually near or higher than some highly specialized degrees/professions (e.g., accounting, computer science, electrical engineering) (Selingo 2017, Webber 2016). Other recent work suggests the importance of broader social skills in career advancement. In the last few decades, the economy yielded higher job growth in occupations that require higher levels of social interaction and stagnated growth in technical work requiring high degrees of analytical and mathematical reasoning, but low levels of social interaction (Deming 2017). Overall, this suggests there are real benefits to acquiring a broad range of knowledge and skills through education and work experiences. A broader range of knowledge and experiences enables individuals to take advantage of job opportunities in other industries or organizations.

There are many studies connecting individuals with broader skillsets, with entrepreneurship or self-employment (Stenard and Sauermann 2016). Prior work suggests that many entrepreneurs are "jacks-of-all-trades" with skills and competencies in many areas, rather than being an elite expert in a narrow area (Lazear 2004). This makes sense because most new ventures do not have the capital to pay a large number of employees for specialized expertise. Thus many entrepreneurs must perform a wide range of job responsibilities including management, sales, accounting, marketing, product development, human resources, and many others—in addition to their central responsibilities developing and implementing the business strategy and acquiring and managing investors. Lazear (2004) finds that this generalist entrepreneurial skillset is derived, in part, from more varied curriculum during college.

This balanced entrepreneurial skillset can also be acquired through varied work experiences throughout a career (Åstebro and Thompson 2011, Wagner 2003). Åstebro and Thompson (2011) find that individuals with a wide range of work experiences from a career history of frequent job-hopping are more likely to become an entrepreneur. Additionally, this high frequency job-switching among entrepreneurs is associated with higher earnings (Campbell et al. 2012), although the association does not hold for non-self-employed wage earners. In the analysis of entrepreneur work histories, I look for variation in the past work experiences for individuals who become startup entrepreneurs. Specifically, I look for variation in the industries and job responsibilities of entrepreneur career paths. Both of these factors facilitate the expansion and variation of an individual's skillset, as they must adjust their work activities to suit the industry and job requirements of each position. The more varied exposure should lead to a more general skillset associated with entrepreneurial activity.

However, it is not clear this generalizable skillset is applicable for the creation of high tech startups. The "jack-of-all-trades" model of entrepreneurship was developed mostly around examining non-high-tech entrepreneurial ventures. As Lazear notes, most entrepreneurs are non-technically skilled individuals starting firms in non-technical fields (Lazear 2004, p.1). Many of the more recent startups have a large technical component central to the business plan. While some technology ventures are launched in the high tech industry, many others are focused around a new technology in a non-technical field (e.g., Uber in the transportation industry). While it is plausible that entrepreneurs still need to have a balance skillset, it is also plausible that high tech entrepreneurs need to be technically skilled—with expertise in a particular domain, application, or technology (Ganco 2013). For example, Mark Zuckerberg, founder and CEO of Facebook, is a highly skilled computer programmer and all his work and academic experiences prior to launching Facebook involved expert-level technical skills. Thus, I will investigate whether high tech entrepreneurs tend to have more technical backgrounds or more varied background in terms of responsibilities and industries.

Moreover, it is unclear whether entrepreneurs can acquire management skills through a broader range of work experience (Cooper and Dunkelberg 1986). At least at the beginning, many entrepreneurs are executives within their new venture, in addition to being the founder. Some prior work suggests that the skills and competencies that make individuals good founders may not translate to management or executive positions. Some research based on workplace surveys shows that founder CEOs are rated as the worst managers of companies by a significant margin (Bennett, Lawrence and Sadun 2016). Also, VC firms and private equity firms often replace founders with professional managers (Hellmann and Puri 2002) and other research shows that firm performance actually improves when VCs replace founders with a hand-picked CEO (Ewens and Marx 2017). There are many factors that might explain why good founders are not always good managers. Ewens and Marx (2017) suggests one factor is that founder CEOs are not fully aware of their weaknesses as managers and consistently overestimate how well managed their firm is. The analysis investigates the prior work experience of entrepreneurs. Consistent with this prior work, entrepreneurs without management experience in their career path may have management gaps that lead to their removal. Thus entrepreneurs' may transition to another position (perhaps another founder position). Conversely, some entrepreneurs might have management experience in their prior work and thus are more likely to remain as a founder CEO as their final job.

Turning to executive and management roles, there is some evidence that management skills require a general management skillset cultivated from prior work experiences. Research finds that the career paths of many Fortune 100 CEOs focus on acquiring general management experience through steady internal promotions and few inter-industry transitions (Koch, Forgues and Monties 2017). Some research suggests there are foundational elements to good management practices that nearly all successful managers must perform. For example, the World Management Survey (WMS) outlines 3 general areas that are core to good management: monitoring, setting targets, and incentives/people management. Good managers promote practices that collect information about intra-firm activity and use that information to make improvements. Managers set targets, track outcomes, and make adjustments to better align targets with outcomes. Managers also institute practices for selecting, evaluating, and rewarding employees based on performance. In short, high-quality management skills involve knowledge and practice about clear managerial objectives. Over their careers, good managers acquire knowledge and experience that enables them to craft practices and strategies for accomplishing these objectives.

Through this view, good management practices are relatively standardized and thus highly transferable between industries. Other research indicates that executives with broader career experience are more likely to benefit from executive job searches and pursue positions in other organizations or industries (Cappelli and Hamori 2014). Thus, one might expect to see large volumes of inter-industry transitions at the executive and senior management level as industries compete for the highest quality managers who can easily transfer their managerial practices. However, a bulk of career transitions occur within an industry, and many open jobs are filled by intra-organizational hires (Keller 2017). Other research indicates that, for executive careers, transitions to jobs with greater pay and managerial responsibility/seniority are often intra-organizational transitions, while external moves often provide similar pay increases but lack career advancement regarding managerial responsibilities (Bidwell and Mollick 2015). Thus, one would expect to see inter-industry transitions involving positions with equal responsibility/seniority.

However, some prior work suggests there is a large variation in the practices of head managers (Bloom and Van Reenen 2007). This research posits management practices are heavily shaped by industry and firm characteristics (Hermalin 1994), psychological traits (Galasso and Simcoe 2011), and "stylistic" preferences of the firm's CEO (Bertrand and Schoar 2003), among other factors. This indicates that one might observe less industry variation in past work experience among those that become executives or senior managers. However, individual and stylistic differences among managers suggests we could see more variation in the job-related responsibilities of prior work experiences of individuals who become executives.

Operationalizing career paths

Abbott and Hrycak (1990) suggest that both theoretical insights and methodological challenges have largely discouraged scholars from analyzing careers as continuous sequences of events (transitions). Theoretically, the structural view of individual careers indicates that transitions are largely influenced by structural conditions (e.g., job vacancies, organizational demographics, industry-specific labor market factors), thus the sequencing of individual job transitions is basically random and largely inconsequential. Other research shows that the timing and duration of work experiences and schedules, which individuals have no control over, can consequentially influence future career decisions, even after controlling for individual and career option attributes (Shah et al. 2014).

Although acknowledging the merit of structural view, the agency view contends that individuals consciously develop plans and shape their work trajectories in response to structural constraints. Thus, from the vantage of the individual, there is a coherent and discernible logic to their career sequence. Furthermore, future job sequencing is, at least in part, influenced by prior job history because individuals create their own futures based on established and culturally acceptable career models (Bertaux 1982). Thus, individuals tend to shape their career paths to match the patterns of familiar careers that have work histories similar to their own histories (Abbott and Hrycak 1990). Methodologically, although there are established methods for analyzing isolated job transitions, career outcomes, and status attainment, there is no standard procedure for analyzing entire career trajectories of sequenced jobs.

More recently, studies have used Optimal matching analysis (OMA) to investigate holistic career trajectories and detect patterns among those sequences (Abbott and Hrycak 1990, Abbott and Tsay 2000, Dlouhy and Biemann 2015, Koch, Forgues and Monties 2017). OMA was most commonly used in the natural sciences to find similarities between proteins or DNA sequences, but the approach has since gained traction among the social sciences. The underlying logic of OMA is to measure the difference between two or more sequences in terms of counting the number of substitutions, insertions, and deletions that are required to transform one sequence into another. Next, these measures of difference are fed into clustering algorithms which yield information on “typical” patterns of sequences (Abbott and Hrycak 1990). In short, the sequences that require the fewest changes (substitutions, insertions and deletions) before becoming identical sequences are grouped together as a distinct pattern. For example, Chan (1995) used OMA to identify four distinct career paths in Hong Kong’s service class. Using OMA, Joseph, Boh, Ang, and Slaughter (2012) identify objective career histories, mobility patterns, and career success of individuals working in the information technology field.

Most of the studies on career trajectories using OMA have relied on survey data with a limited sample size. I develop and refine an alternative procedure for analyzing career trajectories based on network and clustering techniques, which also enables prediction of career outcomes based on prior work history sequencing. The next section describes the data collection and classification process for the job histories, before detailing the procedure for predicting career outcomes.

DATA AND CLASSIFICATION

To model individual career paths, I constructed a database of worker employment histories using individual LinkedIn profiles. I randomly sampled 67,000 individual profiles, which contained self-reported job histories that included job titles, job descriptions, company names, and dates. The individual job histories consisted of 427,054 total jobs (average 6.37 jobs per person). The key challenge with this data source is converting the non-standardized, self-reported job titles and descriptions into meaningful categories.

Next, because LinkedIn user job histories are filled with non-standardized job titles, I grouped the job titles into industry categories using different classification techniques. First, I used approximate string or "fuzzy" matching to classify the user reported job titles into standardized job categories provided by the Bureau of Labor Statistics (BLS). This procedure computes the Levenshtein distance between the normalized word stems of the self-reported job title with the normalized word stems from every BLS job category. This distance is the number of single character edits it would take to transform the self-reported title into the BLS title—and the self-reported title is categorized based on the shortest distance. While this technique accurately classified many of the self-reported titles, the Levenshtein distance was excessively high for many of the self-reported titles, yielding too many errors for manual classification adjustments.

Second, I employed a third-party machine learning classifier to organize job titles and descriptions into 2 levels of standardized industry categories, an industry-level group and sub-industry group (Monkeylearn 2016). There are 17 industry-level categories and 36 sub-industry categories. The third-party classifier was specifically designed to classify professional profiles (e.g. LinkedIn), including company names, jobs titles, and job descriptions, using deep learning based on training data that consists of tens of thousands of LinkedIn profiles. Overall, the classifier yielded an average probability of 0.65 for the classification accuracy of main industry-level category. After inspecting the classification outputs from the fuzzy matching method and the trained industry classifier, it was clear the industry classifier had performed much better, yielding the fewest classification errors. However, to further reduce the number of industry classification errors, I manually reviewed all the industry classifications with a probability below 0.40 to fix any obvious industry classification errors.

Lastly, I used heuristics, based on seniority keywords, to categorize the seniority level of each self-reported job title into 12 seniority-levels. Based on the prior work suggesting the potential transferability of technical or analytical skills (Tambe and Hitt 2013), I developed particular heuristics to distinguish technical staff-level and technical senior staff-level positions from other staff and senior staff positions. In table 1, I reported the 12 seniority-levels and the most common user-reported job titles within each category.

Frequency Distribution of the Seniority-level of Terminal Jobs

Seniority-level categories	Most common job titles	Freq.	Perc.
Executive	president, CEO, CTO, director, vice president	17697	26.4 %
Staff	Consultant; sales (associate, representative); assistant (administrative, executive, legal, research)	15499	23.1 %
Management (junior)	Manager; project manager; account manager; product manager	6258	9.3%
Staff (senior)	senior/principal consultant; senior associate; senior/lead developer	5960	8.9%
Entrepreneur (startup)	Founder; cofounder; founder and CEO	5828	8.7%
Management (senior)	Senior project manager; managing director; managing partner	4009	6.0%
Staff (technical)	software engineer/developer; programmer; engineer; analyst (business, system, financial, data, research)	3854	5.8%
Staff (senior technical)	senior software engineer/developer; senior engineer; senior analyst (business, systems, financial, data)	2085	3.1%
Entrepreneur (self-employed)	Owner; freelance (writer, designer, consultant, photographer, journalist)	1905	2.8%
Other (mentor, board member)	Board member; advisor; mentor	1904	2.8%
Intern-student	intern; student; summer intern; research intern	1574	2.3%
Other (non-tech)	Member; volunteer	427	0.6%
		67000	100%

Table 1: Frequency Distribution of the Seniority-level of Terminal Jobs

In this study, I focused extracting transition insights based on joint industry-level and seniority-level career transitions, which enabled us to investigate inter-industry transitions, as well as seniority transitions. Thus, each job was classified into one of 204 joint category-seniority groups.

Pared (backbone) aggregate network graphs

In order to observe common transition patterns associated with particular career outcomes, I created network graphs of the aggregated careers paths, based on each individual's terminal job. Projecting career paths as network graphs helps visualize which fields have more opportunities and which skills are more transferable. I created 204 aggregate matrices (H) for each of the 204 job classifications (v) that were the terminal job in an individual's career path. I constructed each aggregate matrix (H_v) by combining all normalized individual job transition graphs (G), where edges in the graph represented job transitions and the edge weight (thickness) represented the normalized job tenure in the job to which the transition was made. Each network graph presented is an aggregated matrix (H_v), which allows us to visualize and explore patterns in the career transitions for each of the 204 job classifications.

I created aggregate career path matrices based on the joint industry and seniority level of the individual's final job, and then graphed the matrices to visualize patterns in the career transitions. In each directed network graph (Figures 2-4), the thickness of a given edge (i,j) connecting two nodes (jobs) is weighted by the sum of normalized job tenure of all the individuals who made the transition from i to j and the arrow indicates the direction of the transition. Because of the volume of career transitions, the full aggregate career path networks need to be pared down to observe the "backbones" or dominant paths within the network. I used edge weight filters to keep the connected subgraphs for the highest 10% of edge weights.

To get a sense of the career paths in the database, Table 2 shows the frequency distribution of the seniority-level of the terminal jobs. The most common terminal jobs for individuals in the database are executive and staff positions, each capturing roughly a quarter of terminal jobs. While the large number of executives suggests that the database possibly oversamples more accomplished individuals, the large number of staff positions suggests the sample is still balanced with ordinary employees within firms. In the analysis, I first examine the backbone career path networks for entrepreneurs (startups), executives, and senior management. Next, I explore transition patterns by industry, focusing on the backbone career path networks for entrepreneurs (startups), executives, and senior management in the high tech industry.

Frequency Distribution of the Industry of Terminal Jobs

Industry	Freq.	Perc.
High Tech	19993	29.8%
Corporate	6638	9.9%
Finance	6573	9.8%
Educational	5178	7.7%
Media	5047	7.5%
Arts	3896	5.8%
Medical	3415	5.1%
Manufacturing	3230	4.8%
Recreational	2225	3.3%
Non-profit	2130	3.2%
Legal	2089	3.1%
Consumer Goods	1912	2.9%
Construction	1303	1.9%
Service	1274	1.9%
Government	1209	1.8%
Transportation	788	1.2%
Agriculture	102	0.2%
	67000	100%

Table 2: Frequency Distribution of the Industry of Terminal Jobs

Approximately 30% of the careers in the database reported that their last transition was to the high tech industry, which was highest among all industries. Although online career social networking sites are a useful tool for employees of all industries, these new tools are heavily used in technology and other digitally focused sectors. Thus it is not surprising that the high tech industry is strongly represented in the database. Other than high tech, the most common industries of the terminal jobs for individuals were corporate, finance, and education (see Table 2). Although I focus on the high tech sector, I also make comparisons with other industries (e.g., corporate, finance, media) to show how some career transition patterns are distinct within the high tech field. Specifically, I investigate patterns in the high tech sector to explore associations between technical skills and inter-industry transitions, extending prior work on skill transferability in the IT sector (Tambe and Hitt, 2013). While I detail many insights yielded from these career transition networks by industry, Table 3 lists the most common transitions for individuals with each industry-seniority terminal job.

Most Common Job Transitions by Industry-Seniority Outcomes

Outcome	Common Transitions
High Tech-entrep-startup	Hi-ts, [Hi-ts, Hi-jm, Hi-ex], Me-en, Cor-en, Ar-en, Ed-en, [Hi-ts, Hi-s], [Hi-ts, Hi-jm], [Hi-ts, Hi-sts], Fi-en
High Tech-executive	[Hi-ts, Hi-jm], Cor-ex, Me-ex, [Hi-ts, Hi-jm, Hi-sm], Hi-ss, [Hi-ts, Hi-sts], Fi-ex, [Hi-ts, Hi-en]
High Tech-management-senior	[Hi-ts, Hi-jm], [Hi-ts, Hi-sts], [Hi-ts, Hi-ss], [Hi-jm, Hi-ex], Hi-ts, Cor-sm, Me-sm
Corporate-entrep-startup	Cor-ex, Me-en, No-en, Hi-en, Cor-s, Fi-ex, Fi-en, CG-en, Me-ex, Ar-en
Corporate-executive	[Cor-jm, Me-ex], Cor-jm, Hi-ex, Le-ex, Fi-ex, Cor-ss, Cor-s, Ed-ex, Ar-ex
Corporate-management-senior	Cor-jm, Cor-ss, [Cor-jm, Cor-ex], Me-sm, Hi-jm, Cor-s, Hi-sm, Le-sm
Finance-entrep-startup	Fi-ex, [Fi-ts, Fi-s], Fi-jm, Cor-en, Hi-en, Ed-en, Fi-ss, Hi-ex
Finance-executive	Fi-s, Fi-sm, Fi-jm, [Fi-s, Fi-ss], Cor-ex, [Fi-s, Fi-jm], Le-ex, Me-ex, Hi-ex
Finance-management-senior	[Fi-s, Fi-ex], [Fi-s, Fi-ss], [Fi-ts, Fi-s], Fi-jm, Fi-ts, Le-sm, Cor-sm
Educational-entrep-startup	[Ed-s, Ed-ex], Se-en, Hi-en, No-vol, Ed-vol, Ed-s, Go-en, No-en, Le-en, Ed-jm, Se-ex
Educational-executive	Ed-s, [Ed-s, Ed-vol], No-ex, Se-ex, Me-ex, Md-ex, Ed-ss, Hi-ex
Educational-management-senior	[Ed-ex, Me-sm], Cor-ex, Ed-ss, Fi-sm, Hi-ex, Ed-ex
Media-entrep-startup	[Me-ss, Me-ex], Hi-en, Ar-en, Me-s, [Me-s, Me-jm], Fi-en, Ed-en, Hi-ex, Me-i,
Media-executive	Me-s, Me-jm, Cor-ex, Hi-ex, Ar-ex, Me-ss, Me-en, Fi-ex, Ed-ex, Hi-ss
Media-management-senior	[Me-s, Me-ex], Me-jm, Me-ss, Hi-sm, Hi-ex, Ar-ss, Me-s, Le-sm, Hi-jm
Arts-entrep-startup	Ar-ex, [Ar-s, Ar-vol], Me-ex, Me-en, Ed-en, Hi-en, Se-en, [Me-s, Ar-s], Ar-ss
Arts-executive	Me-ex, [Ar-s, Ar-esp], Ed-ex, Ar-s, Re-ex, Ar-ss, Se-ex, Ar-en
Arts-management-senior	Re-sm, Ar-ex, Ma-s, Ar-s, [Ar-vol, Ar-ss], [Ar-jm, Me-sm], [Ar-vol, Ar-jm], Cor-sm
Medical-entrep-startup	Md-ex, Ed-en, Le-ex, Hi-en, Se-en, Se-s, Me-s, No-ss, No-sm
Medical-executive	Ed-ex, Md-s, No-ex, [Md-s, Md-vol], Cor-ex, Md-ss, Ma-ex, Hi-ex, Se-ex, Md-jm
Medical-management-senior	[Md-ss, Md-ex], Md-ss, Md-jm, Cor-sm, [Md-vol, Md-jm]

Abbreviations: Arts-entrep-startup: Ar-en, Arts-executive: Ar-ex, Arts-management-senior: Ar-sm, Corporate-entrep-startup: Cor-en, Corporate-executive: Cor-ex, Corporate-management-junior: Cor-jm, Corporate-management-senior: Cor-sm, Corporate-other-nontech: Cor-vol, Educational-entrep-startup: Ed-en, Educational-executive: Ed-ex, Educational-management-senior: Ed-sm, Educational-other-nontech: Ed-vol, Finance-entrep-startup: Fi-en, Finance-executive: Fi-ex, , Finance-management-senior: Fi-sm, Finance-staff-senior: Fi-ss, High Tech-entrep-startup: Hi-en, High Tech-executive: Hi-ex, High Tech-management-junior: Hi-jm, High Tech-management-senior: Hi-sm, High Tech-staff-senior-tech: Hi-sts, Media-entrep-startup: Me-en, Media-executive: Me-ex, Media-management-senior: Me-sm, Medical-entrep-startup: Md-en, Medical-executive: Md-ex, Medical-management-senior: Md-sm, Medical-other-nontech: Md-vol, Medical-staff: Md-s

Table 3: Most Common Job Transitions by Industry-Seniority Outcomes

RESULTS: TRANSITIONS INSIGHTS IN HIGH TECH INDUSTRY

Entrepreneurs

First, I extract insights based on entrepreneurs in the high tech industry. For a job to be classified as startup entrepreneur, the job titles had to include "founder" or "co-founder", although many titles included an executive role as well (e.g., "founder and CEO"). High tech was the most popular industry among persons whose terminal transition was to entrepreneurship. Figure 2 shows the dominant career paths or "network backbones" for individuals whose terminal job is high tech entrepreneur. The edge thickness between job categories captures how common each pairwise transition was among all high tech entrepreneurs.

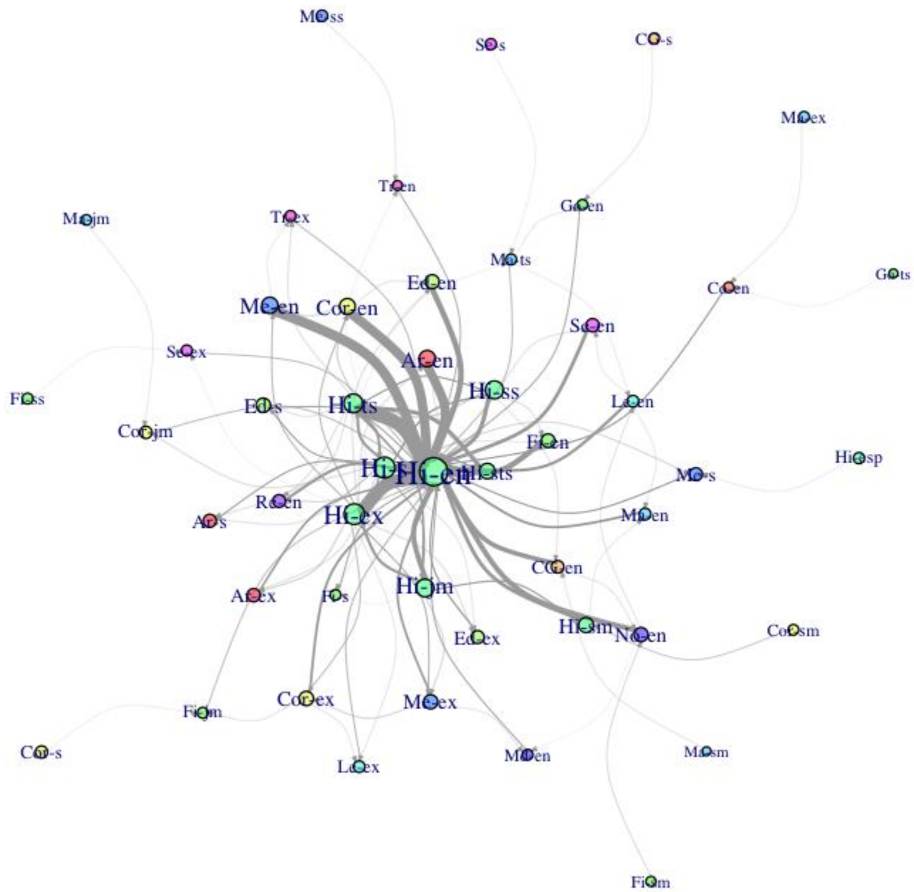
I find that intra-industry transitions are very common and most high tech entrepreneurs have some previous work experience using technical skills. The most common transitions are from high tech technical staff and high tech executives. Another common path corresponds to a technical skills transition to entrepreneurship, as individuals transition from technical staff, to senior technical staff, to entrepreneurs. I find that technical work experience is much less common for the career paths of entrepreneurs in other industries (e.g. corporate, media, education). The jump from technical staff roles is intuitive, as entrepreneurship in the high tech field often involves deep understanding or expertise of a technology, which is facilitated by direct training and work experience with a technology as a programmer, engineer, or analyst. One potential explanation is that technical staff positions are filled by skilled persons that can create the content, infrastructure, or ideas that enables new businesses. Persons transitioning from executive roles to entrepreneurship have valuable leadership and management skills and have likely pursued some services-oriented venture or are co-founding the new venture with a more technically-skilled co-founder.

Moreover, entrepreneurship is a risky career transition. Most people consider the opportunity cost of pursuing new opportunities (Amit, Muller and Cockburn 1995, Reynolds 1987)—that is, whether the opportunity cost is higher or lower than their current compensation and job satisfaction. Thus ambitious and highly skilled lower-level technical staff have lower opportunity costs and might be disproportionally attracted to starting their own high tech venture. This tendency is likely exaggerated when there is a mismatch between the individual's skills and abilities and their job responsibilities (Stenard and Sauermann 2016). This mismatch tends to result in a poor wage (relative to skills) and in turn encourage worker transition to entrepreneurship (Åstebro and Thompson 2011). Additionally, the transition from executive roles to entrepreneurship makes sense, in light of prior research showing that the probability of creating a new venture is higher if the individual has great capital (Evans and Leighton 1989) or more transferable experience (Cooper, Woo and Dunkelberg 1989).

Another one of the more common paths involve a mix of technical and management experience, as individuals switch from technical staff, to junior managers, to executives, to entrepreneurs. The individuals with both technical and management experience are perhaps best suited to be a "jack-of-all-trades" that can handle the many job responsibilities perform by founders at the early stages. Regarding management skill transitions, I observe relatively few transitions from pure "management tracks" where individuals transition from junior management to senior management before launching a new high tech venture.

Another interesting finding is that the two most common paths to entrepreneurship involve short or long paths, suggesting that many entrepreneurs are either younger or older. One path involves, a quick jump into entrepreneurship after 1-2 transitions from technical staff or staff positions, which likely corresponds to relatively younger entrepreneurs. This path fits the popular press depiction of Silicon Valley startups launched by young computer science experts (e.g., Mark Zuckerberg, Founder of Facebook at age 20). However, another equally common career path involves many career transitions, often involving a mix of technical work, junior management positions, and potentially even some executive experience before the individual makes jump into entrepreneurship. These individuals are likely middle age industry veterans with large stocks of human and social capital accumulated through years of work. This finding seems consistent with recent work suggesting that most successful entrepreneurs are middle age (mean age of 42), which contrasts with the public perception of the young and inexperienced high tech entrepreneurs in his/her 20s or early 30s (Azoulay et al. 2017).

I also find that many entrepreneurs are serial entrepreneurs, both within and between industries. Among the most common inter-industry transitions, I find that many high tech entrepreneurs are serial entrepreneurs transitioning from other industries including media, corporate, arts, and education. Looking at entrepreneurs in other industries, I find that many high tech entrepreneurs transitioned to become entrepreneurs in fields like corporate, finance, media, and medical.



Abbreviations: Arts-entrep-startup: Ar-en, Arts-executive: Ar-ex, Arts-management-senior: Ar-sm, Corporate-entrep-startup: Cor-en, Corporate-executive: Cor-ex, Corporate-management-junior: Cor-jm, Corporate-management-senior: Cor-sm, Corporate-other-nontech: Cor-vol, Educational-entrep-startup: Ed-en, Educational-executive: Ed-ex, Educational-management-senior: Ed-sm, Educational-other-nontech: Ed-vol, Finance-entrep-startup: Fi-en, Finance-executive: Fi-ex, , Finance-management-senior: Fi-sm, Finance-staff-senior: Fi-ss, High Tech-entrep-startup: Hi-en, High Tech-executive: Hi-ex, High Tech-management-junior: Hi-jm, High Tech-management-senior: Hi-sm, High Tech-staff-senior-tech: Hi-sts, Media-entrep-startup: Me-en, Media-executive: Me-ex, Media-management-senior: Me-sm, Medical-entrep-startup: Md-en, Medical-executive: Md-ex, Medical-management-senior: Md-sm, Medical-other-nontech: Md-vol, Medical-staff: Md-s

Figure 2: Backbone Aggregate Career Transition Network of High Tech Startup Entrepreneurs

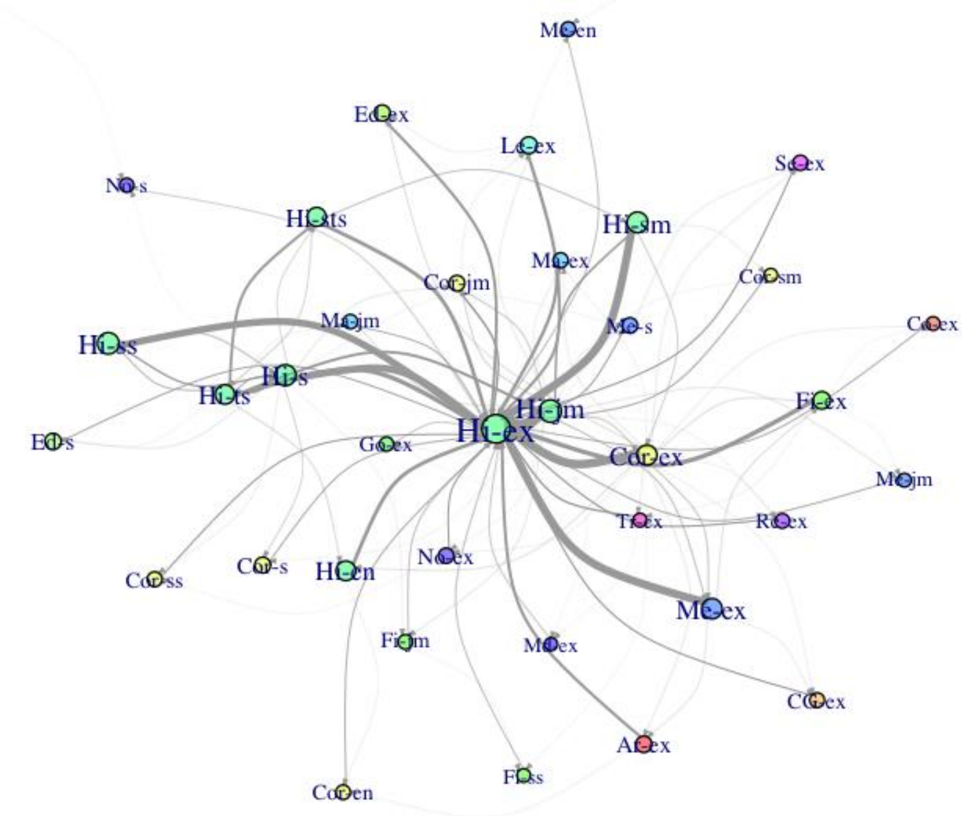
Executives

Next, I investigated the aggregate network graph for individuals whose last job was executive. The most common job titles for executive positions include CEO or CTO. Overall, approximately a quarter of the final jobs in the database were executive jobs and they were largely spread out among industries. Those whose last transition was to executive and/or high-tech had the largest indegree followed by corporate, media, educational, and finance.

Figure 3 shows the pared aggregate network graph for individuals whose last job was high tech executive. Intra-industry transitions are common among high tech executives and I observe that many individuals have prior experience in technically skilled positions. I find the most common path involved a mix of technical and management skills, where individuals frequently switched from a technical staff positions to junior management positions before finally transitioning to an executive position with a high tech firm. Although the transition from junior manager was more common than the transition from senior manager, I find that some high tech executives also come from a traditional management track, transitioning from junior management to senior management and then on to an executive post. However, many of these individuals worked in the technical staff position prior to moving their way up the management ladder. One explanation is having technical experience gives individuals valuable knowledge for managing technical projects and technical staff, which are often vital to high tech firms. For example, technical experience facilitates understanding of the complexity of technical projects, enabling these individuals to assign the appropriate resources and attention needed to increase the likelihood of success.

The transferability of management skills across industries is also prominent among high tech executives. Many high tech executive positions are commonly filled by persons horizontally transferring industries—from another executive position in the corporate and media industries. Prior to their final transition to high tech, many of these corporate and media executives were junior managers in the high tech industry. This suggests there are potential benefits to switching industries, enabling managers to acquire outside knowledge which they can apply if they choose to return to the high tech industry.

I also observed a clear "technical track" to executive positions, in which individuals transition from technical staff, to senior technical staff, to high tech executives. A closer look at the data reveals these tracks often lead to positions as Chief Technology Officer (CTO). Another common path to high tech executive involves prior transitions from technical staff to entrepreneur, and then from entrepreneur to executive. This finding is consistent with the "jack-of-all-trades" view of the entrepreneur. Running your own firm gives you experience at a diverse range of job responsibilities, which can give you valuable insights into managing different departments as an executive of a firm.



Abbreviations: Arts-entrep-startup: Ar-en, Arts-executive: Ar-ex, Arts-management-senior: Ar-sm, Corporate-entrep-startup: Cor-en, Corporate-executive: Cor-ex, Corporate-management-junior: Cor-jm, Corporate-management-senior: Cor-sm, Corporate-other-nontech: Cor-vol, Educational-entrep-startup: Ed-en, Educational-executive: Ed-ex, Educational-management-senior: Ed-sm, Educational-other-nontech: Ed-vol, Finance-entrep-startup: Fi-en, Finance-executive: Fi-ex, , Finance-management-senior: Fi-sm, Finance-staff-senior: Fi-ss, High Tech-entrep-startup: Hi-en, High Tech-executive: Hi-ex, High Tech-management-junior: Hi-jm, High Tech-management-senior: Hi-sm, High Tech-staff-senior-tech: Hi-sts, Media-entrep-startup: Me-en, Media-executive: Me-ex, Media-management-senior: Me-sm, Medical-entrep-startup: Md-en, Medical-executive: Md-ex, Medical-management-senior: Md-sm, Medical-other-nontech: Md-vol, Medical-staff: Md-s

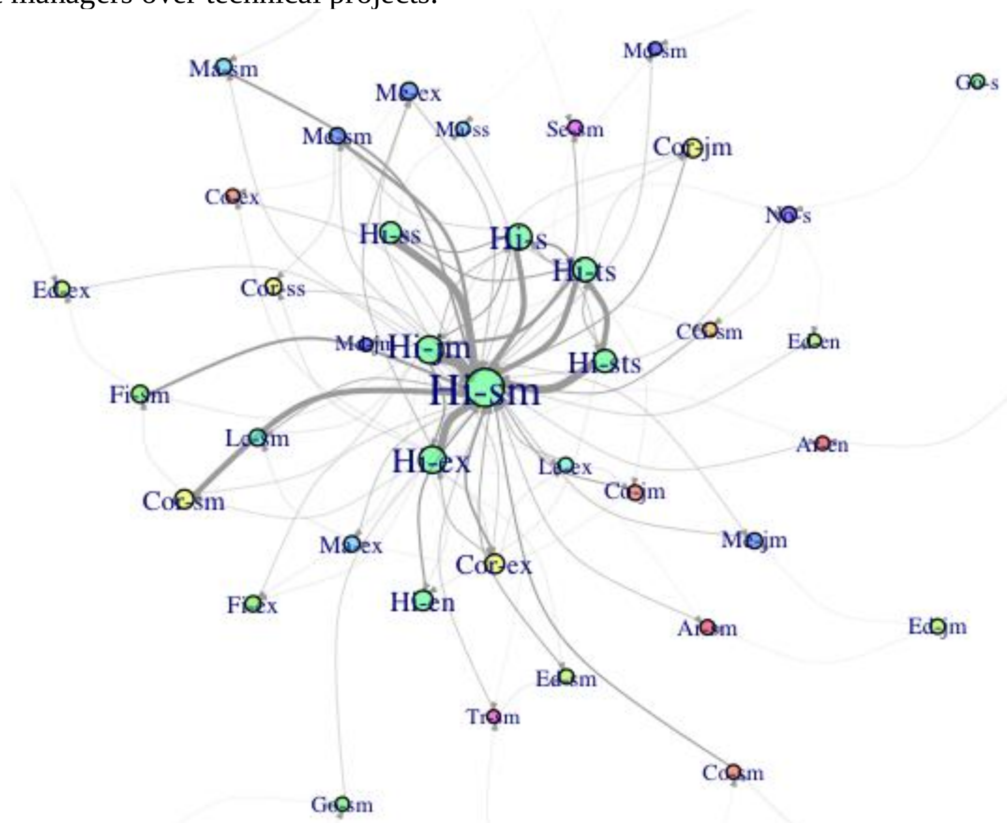
Figure 3: Backbone Aggregate Career Transition Network of High Tech Executives

Senior managers

Figure 4 graphs the common career transitions for senior managers in the high tech industry. Common job titles for senior management include senior project manager and senior product manager. Intra-industry transitions to senior management positions in the high tech field are much more common than inter-industry transitions. I find that most transitions to senior managers involve a transition from technical staff somewhere along the career path. One common career path includes transitioning from technical staff to junior management or senior staff before a final transition to senior management. Another path includes transitioning from technical staff to senior technical staff to senior management. Moreover, I find many transitions from senior staff, executive, and technical staff to senior management. I also find many lateral inter-industry transitions from senior management positions in corporate and media. However, many of these corporate and media senior managers had previously worked as junior managers in the high tech field, thus ultimately returning to their experience in the high tech industry.

For comparison, I examined the common career paths for senior managers in other industries like corporate, media, education, and finance. With the exception of finance, in these other industries the common paths followed typical “management tracks” in which many individuals transition from staff to junior managers to senior managers within an industry. Although not as common as the high tech industry, many finance senior managers had previously worked in a technical staff position. Outside the high tech industry, few of the junior managers had technical staff experience prior to the latest transition to senior management.

On the one hand, the prevalence of technical backgrounds for individuals in senior management positions is surprising because exceling in technical positions does not necessarily translate to skills in managing people. On the other hand, managers that have the most technical understanding are most capable of managing technical projects and technical talent in the firm. Many of the internal projects inside a high tech firm may involve a deeper understanding of an underlying technology or process, or more frequent interaction with technical experts—thus making technical knowledge important when selecting senior managers. This potential explanation is supported when I looked at the specific job titles and job descriptions of senior managers with prior technical experience and observed that many were IT/systems managers or project managers over technical projects.



Abbreviations: Arts-entrep-startup: Ar-en, Arts-executive: Ar-ex, Arts-management-senior: Ar-sm, Corporate-entrep-startup: Cor-en, Corporate-executive: Cor-ex, Corporate-management-junior: Cor-jm, Corporate-management-senior: Cor-sm, Corporate-other-nontech: Cor-vol, Educational-entrep-startup: Ed-en, Educational-executive: Ed-ex, Educational-management-senior: Ed-sm, Educational-other-nontech: Ed-vol, Finance-entrep-startup: Fi-en, Finance-executive: Fi-ex, , Finance-management-senior: Fi-sm, Finance-staff-senior: Fi-ss, High Tech-entrep-startup: Hi-en, High Tech-executive: Hi-ex, High Tech-management-junior: Hi-jm, High Tech-management-senior: Hi-sm, High Tech-staff-senior-tech: Hi-sts, Media-entrep-startup: Me-en, Media-executive: Me-ex, Media-management-senior: Me-sm, Medical-entrep-startup: Md-en, Medical-executive: Md-ex, Medical-management-senior: Md-sm, Medical-other-nontech: Md-vol, Medical-staff: Md-s

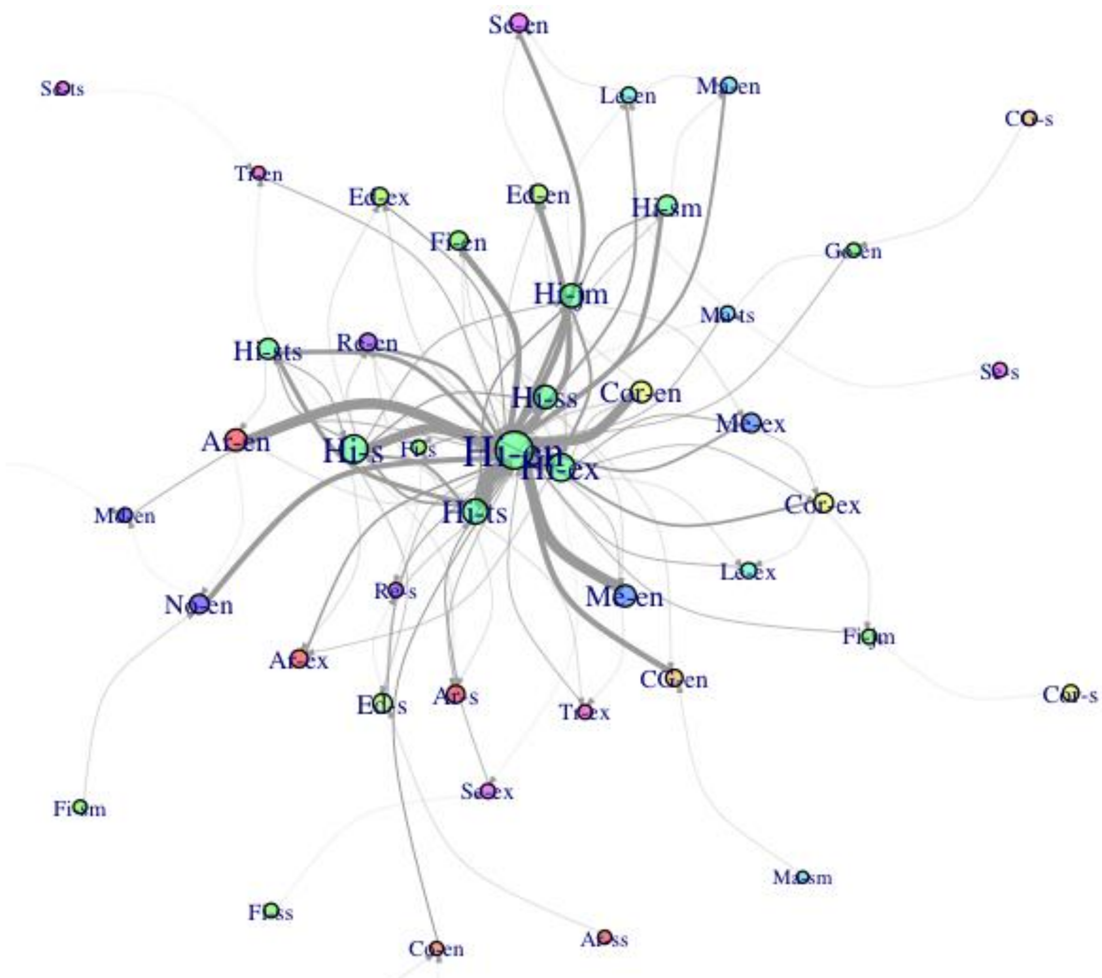
Figure 4: Backbone Aggregate Career Transition Network of High Tech Senior Management

Gender Differences Career Paths

Male and Female High Tech Entrepreneurs

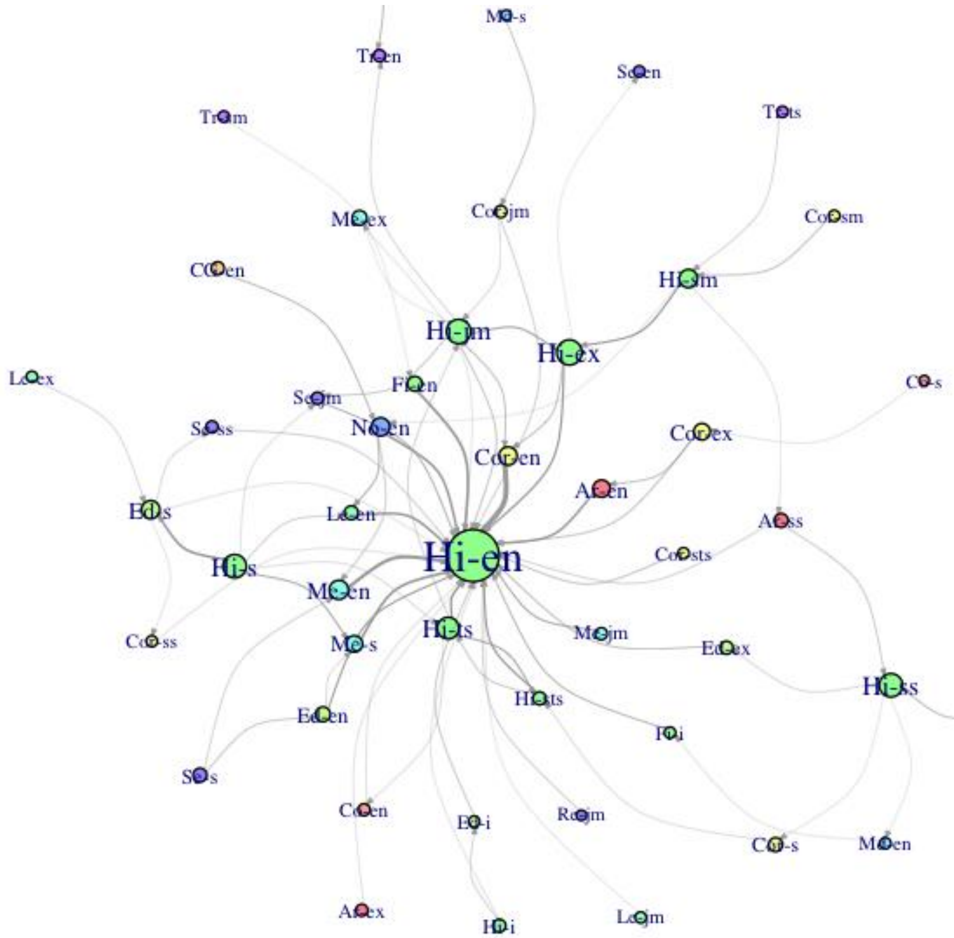
I observe differences in the common career paths of male and female entrepreneurs in the high tech industry (see Figures 5 and 6). We find that males are more likely to make the transition to high tech entrepreneur from another job within the high tech industry. The most common intra-industry transitions were from technical staff, executive, and staff. While the transitions for males were more concentrated among particular paths, the paths for female entrepreneurs are more evenly dispersed among many positions both within and outside the industry. For female entrepreneurs, the most common transitions were entrepreneurs from other industries, particularly corporate, media, finance, and legal. Tracing the paths back further, we see that many of these women were often serial entrepreneurs that launch startups in many fields. Overall, we observe the career paths of high tech female entrepreneurs involve broader industry experience. We also find that many of these women have work experience in the high tech sector somewhere along their career path. Among transitions from within the high tech sector, which were fairly common, we find that technical staff, senior technical staff, and executive positions were most prominent.

One interpretation of these findings is that females have broader interest in opportunities in other industries, and this outside experience enables them to see entrepreneurial opportunities in many variety industries including high tech. This explanation is consistent with the idea of structural holes in networked relations, which gives brokers "vision advantages" as a result of spanning the different communities between industries (Burt 2004). Alternatively, women could be experiencing some resistance starting venturing within the high tech sector, an industry shown to disproportionately fund and support male entrepreneurial teams (Ruef, Aldrich and Carter 2003). In turn, these women might earn respect by launching startups in other industries, and then received more support with returning with an idea for a high tech venture.



Abbreviations: Arts-entrep-startup: Ar-en, Arts-executive: Ar-ex, Arts-management-senior: Ar-sm, Corporate-entrep-startup: Cor-en, Corporate-executive: Cor-ex, Corporate-management-junior: Cor-jm, Corporate-management-senior: Cor-sm, Corporate-other-nontech: Cor-vol, Educational-entrep-startup: Ed-en, Educational-executive: Ed-ex, Educational-management-senior: Ed-sm, Educational-other-nontech: Ed-vol, Finance-entrep-startup: Fi-en, Finance-executive: Fi-ex, , Finance-management-senior: Fi-sm, Finance-staff-senior: Fi-ss, High Tech-entrep-startup: Hi-en, High Tech-executive: Hi-ex, High Tech-management-junior: Hi-jm, High Tech-management-senior: Hi-sm, High Tech-staff-senior-tech: Hi-sts, Media-entrep-startup: Me-en, Media-executive: Me-ex, Media-management-senior: Me-sm, Medical-entrep-startup: Md-en, Medical-executive: Md-ex, Medical-management-senior: Md-sm, Medical-other-nontech: Md-vol, Medical-staff: Md-s

Figure 5: Backbone Aggregate Career Transition Network of Male High Tech Startup Entrepreneurs

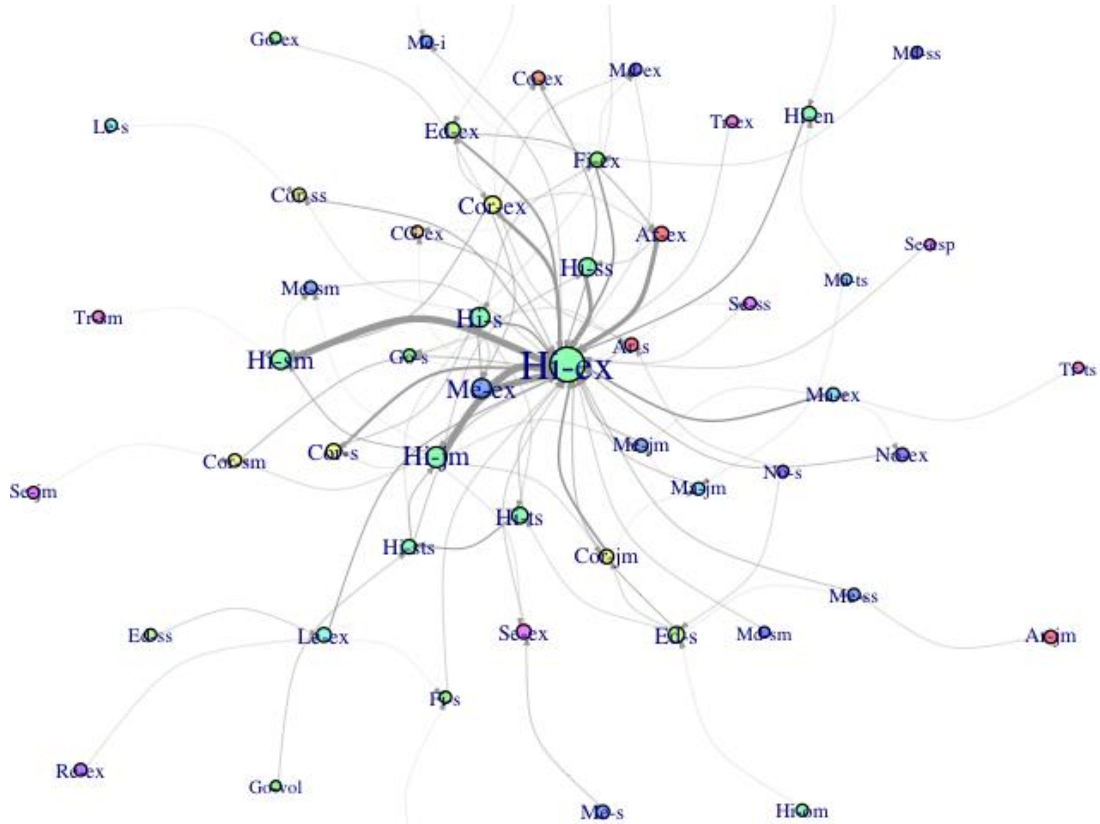


Abbreviations: Arts-entrep-startup: Ar-en, Arts-executive: Ar-ex, Arts-management-senior: Ar-sm, Corporate-entrep-startup: Cor-en, Corporate-executive: Cor-ex, Corporate-management-junior: Cor-jm, Corporate-management-senior: Cor-sm, Corporate-other-nontech: Cor-vol, Educational-entrep-startup: Ed-en, Educational-executive: Ed-ex, Educational-management-senior: Ed-sm, Educational-other-nontech: Ed-vol, Finance-entrep-startup: Fi-en, Finance-executive: Fi-ex, , Finance-management-senior: Fi-sm, Finance-staff-senior: Fi-ss, High Tech-entrep-startup: Hi-en, High Tech-executive: Hi-ex, High Tech-management-junior: Hi-jm, High Tech-management-senior: Hi-sm, High Tech-staff-senior-tech: Hi-sts, Media-entrep-startup: Me-en, Media-executive: Me-ex, Media-management-senior: Me-sm, Medical-entrep-startup: Md-en, Medical-executive: Md-ex, Medical-management-senior: Md-sm, Medical-other-nontech: Md-vol, Medical-staff: Md-s

Figure 6: Backbone Aggregate Career Transition Network of Female High Tech Startup Entrepreneurs

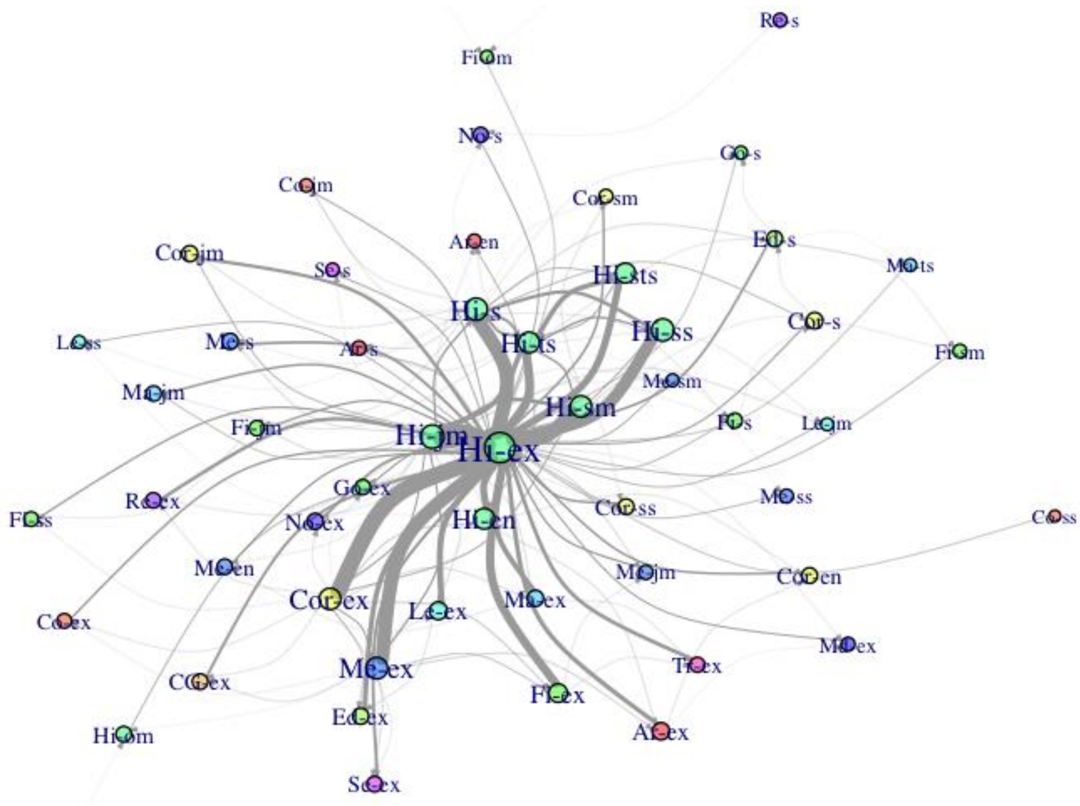
Male and Female High Tech Executives

Figure 7 and Figure 8 illustrate the common career paths for female and male executives in the high tech sector. While many of the common transitions were similar among male and female executives, one important difference is the ranking and scale of those transitions. For example, relative to female executive, male executives are much more likely to come from less senior roles like junior manager or staff. This is consistent is prior work on gender differences in executives climbing the corporate ladder. For example, in a comparative study of women and male executives, women reported facing stronger barriers to being promoted to executive level positions—relying heavily on a longer track record for advancement relative to their male counterparts (Lyness and Thompson 2000). One explanation offered is the women are commonly excluded from informal network where social bonds are formed and influential in promotion decisions (Williams, Muller and Kilanski 2012). The most common transition for female executives are media executives and high tech senior management, and for male executives they were corporate executive and high tech junior management.



Abbreviations: Arts-entrep-startup: Ar-en, Arts-executive: Ar-ex, Arts-management-senior: Ar-sm, Corporate-entrep-startup: Cor-en, Corporate-executive: Cor-ex, Corporate-management-junior: Cor-jm, Corporate-management-senior: Cor-sm, Corporate-other-nontech: Cor-vol, Educational-entrep-startup: Ed-en, Educational-executive: Ed-ex, Educational-management-senior: Ed-sm, Educational-other-nontech: Ed-vol, Finance-entrep-startup: Fi-en, Finance-executive: Fi-ex, , Finance-management-senior: Fi-sm, Finance-staff-senior: Fi-ss, High Tech-entrep-startup: Hi-en, High Tech-executive: Hi-ex, High Tech-management-junior: Hi-jm, High Tech-management-senior: Hi-sm, High Tech-staff-senior-tech: Hi-sts, Media-entrep-startup: Me-en, Media-executive: Me-ex, Media-management-senior: Me-sm, Medical-entrep-startup: Md-en, Medical-executive: Md-ex, Medical-management-senior: Md-sm, Medical-other-nontech: Md-vol, Medical-staff: Md-s

Figure 7: Backbone Aggregate Career Transition Network of Female High Tech Startup Executives



Abbreviations: Arts-entrep-startup: Ar-en, Arts-executive: Ar-ex, Arts-management-senior: Ar-sm, Corporate-entrep-startup: Cor-en, Corporate-executive: Cor-ex, Corporate-management-junior: Cor-jm, Corporate-management-senior: Cor-sm, Corporate-other-nontech: Cor-vol, Educational-entrep-startup: Ed-en, Educational-executive: Ed-ex, Educational-management-senior: Ed-sm, Educational-other-nontech: Ed-vol, Finance-entrep-startup: Fi-en, Finance-executive: Fi-ex, , Finance-management-senior: Fi-sm, Finance-staff-senior: Fi-ss, High Tech-entrep-startup: Hi-en, High Tech-executive: Hi-ex, High Tech-management-junior: Hi-jm, High Tech-management-senior: Hi-sm, High Tech-staff-senior-tech: Hi-sts, Media-entrep-startup: Me-en, Media-executive: Me-ex, Media-management-senior: Me-sm, Medical-entrep-startup: Md-en, Medical-executive: Md-ex, Medical-management-senior: Md-sm, Medical-other-nontech: Md-vol, Medical-staff: Md-s

Figure 8. Backbone Aggregate Career Transition Network of Male High Tech Startup Executives

Other industries

I draw several insights based on the observation from career transitions for entrepreneurs, executives, and senior managers in various industries. Regarding high tech and finance entrepreneurs, I observe more intra-industry transitions to entrepreneurship and a sizable portion of these entrepreneurs have technical or executive experience in their career paths. One explanation is that both high tech and finance industries require specialized and technical knowledge that can be barriers to inter-industries players stepping in with an innovative new-venture idea. In all the industries except media, I observe few transitions from senior management, and common transitions from executive, senior staff, and staff positions. This suggests that entrepreneurs tend to avoid management tracks and, given the age associations with staff and executive positions, often start companies early or later in their career trajectory (younger and older entrepreneurs) (Azoulay et al. 2017).

Entrepreneurs transitioning from another industry tend to be serial entrepreneurs or staff. I observe more inter-industry transitions for entrepreneurs in medical and corporate. This makes sense, particularly in the medical field where medical training is very formal, standardized, and regulated, which are not exactly drivers of disruptive business innovations. While medical research certain make medical innovations, the fruits of the research are usually commercialized by business-focused entrepreneurs. High tech entrepreneurs seem to be the most transferable to other industries, appearing in the common paths for entrepreneurs in media, medical, education, finance, and arts.

Turning to executives, inter-industry executive to executive transitions where highly common in all industries. Inter-industry transitions are particularly common among corporate and media executives. I also observe transitions from media executives were especially common among executives in corporate and the arts. Altogether, these observations suggest the executive skill set is highly transferable across industries and becomes more valuable (transferable) based on the diversity of industry experience.

Among intra-industry career paths to executives, I observe relatively few transitions from junior or senior management except in corporate and finance industries where common transitions were from junior management and senior staff. In the high tech industry, I observe an interesting common path where individuals acquire a mix of both technical and junior management experience on the way to becoming an executive. In media, medical, and education, the common transitions were from staff and senior staff.

Last, the analysis of senior management transition suggests these career paths are the most straightforward and intuitive. In most industries, I observe many intra-industry linear transitions from staff, to senior staff or junior management, to senior management. Intra-industry transitions are relatively more common than inter-industry transitions in medical and finance industries. In addition to upward career transitions to more senior positions, several career paths involve transitions to positions with lower seniority. I observe several common intra-industry paths from executive to senior management in medical, corporate, finance, arts, and education. This could be people branching out from bigger firms to test their skills running a small business or startup—and then returning from the chaos to the stability of established enterprises. Moreover, lateral senior management transitions from senior management position in other industries is also a common path in high tech, media, corporate, finance, arts, and education. Among these transitions, one that stands out is the legal senior managers to high tech, media, corporate, and finance senior managers. One explanation could be the persistent stalled employment growth in the legal field, which reduces career opportunities for advancement (i.e. legal partnerships), thus encouraging incredibly smart legal talent to adapt skills and pursue advancement growing industries.

Overall, I have discussed several insights regarding common career transitions of entrepreneurs, executives, and senior management. These insights can inform managers' decision making process during the recruitment and hiring process for new positions, potentially considering non-traditional applicants from different industry and skill experiences. Conversely, these insights are helpful for career coaches, academic counselors, and individuals in the labor market (or about to enter the market) who are eager to understand the career paths that will improve the likelihood of reaching their career goals. Next, I test these insights by predicting an individual's next job using a variety of methods.

TESTING OBSERVATIONS: PREDICTION METHODS

In this study, I focused extracting transition insights based on joint industry-level and seniority-level career transitions, which enabled us to investigate inter-industry transitions, as well as seniority transitions. Thus, each job was classified into one of 204 joint category-seniority groups. Next, I randomly sampled 50,000 careers for the training data set. I created 204 aggregate matrices (H) for each of the 204 job classifications (v) that were the terminal job in an individual's career path. I constructed each aggregate matrix (Hv) by combining all normalized individual job transition graphs (G), where edges in the graph represented job transitions and the nodes represented the tenure in the job to which transition was made. The network graphs presented in the aggregated matrix (Hv) allows us to visualize and explore patterns in the career transitions for each of the 204 job classifications.

I developed various methods to test prediction accuracy of the next job, for an individual, based on the available aggregate matrices for job classification. Using a test sample of 20,000 individuals, I evaluated the performance using 3 techniques 1) network backbone identification, 2) k-Nearest Neighbors (k-NN), and 3) artificial neural networks. Next, I randomly sampled 20,000 careers for the test set among the remaining individuals. For the network "backbone" approach, I predicted next job outcome as identified using max(Gi*Hv). Based on 10,000 repeated draws of the randomly sampled test data set, I found the overall accuracy of 40.45% using this method (see Table 4). The accuracy when considering the top 2 or top 3 values in the dot-product (Gi*Hv), I found the accuracy of this backbone technique to be 68.03% (see Table 4).

Using the prediction method based on k-nearest neighbors (k-NN) approach of minimizing the distance between an individual's predicted career outcomes (as measured by the dot product Gi*Hv) and actual career outcome for individuals in the training set. To achieve this, I took the randomly sampled training set and recreated the aggregate matrices (H), as explained above, but this time with the last job of individuals removed from the data. I then used these training matrices to compute the dot products (Gi*Hv) and identified test set individuals that had the shortest Euclidean distance. Since the actual job outcome of the training set individuals is known, the prediction was the job outcome with the shortest average distance. In Table 4, I report the overall accuracy for the k-NN approach based on Euclidean distance. The k-NN with Euclidean distance performed the best, with an overall accuracy of 45.14% (see Table 4).

To further enhance the prediction accuracy of the model, I used a neural network approach by training the model using a simple learning model with single hidden layer of linear weights to adjust the probability of failures. Thus, the updated Ho could be written as:

$$H_o = \sum_{i \in I} w_o . h_i \mid (i_{t+1} = o)$$

$$Where\ w_o = \frac{\frac{1}{2}\left(1 + \left(\frac{max_o(h_i.H_o)}{h_i.H_o}\right)\right)}{\sum_o \frac{1}{2}\left(1 + \left(\frac{max_o(h_i.H_o)}{h_i.H_o}\right)\right)}$$

Here the weights are updated as each individual in training set is added in the aggregate matrix. This weighting system boosted overall accuracy. I found the overall accuracy of 47.63% using this method (see Table 4).

Accuracy in Predicting Next Job

Method	Accuracy
Weighted probabilistic prediction	13.7%
Network Backbone (max q-score)	39.55%
k-NN (Euclidean distance)	45.14%
Neural network weights	47.63%

Table 4. Accuracy in Predicting Next Job

DISCUSSION: MANAGERIAL INSIGHTS

This is the first study, to the best of my knowledge, that uses large volume of data from a professional networking platform to identify career transition insights and validate their predictive power using career paths of 67,000 professionals. Focusing the analysis on the career paths of entrepreneurs, executives, and senior management in the high tech industry, I highlight common patterns in career trajectories. These empirically identified and validated career transition insights are very important, especially in a highly dynamic and technology oriented labor market, for strategic career planning and management.

I find that many high tech entrepreneurs and executives have technical or analytical backgrounds in their work history and one of the more common paths includes a mix of technical and managerial work experience prior to becoming an entrepreneur. I also find that the entrepreneur and executive skillsets seem highly transferable across industries. This is supported by the high volume of serial entrepreneurs that switch industries to start/launch another venture and the high frequency of executive to executive transitions between industries. As discussed in prior literature, it was interesting to see how positions involving technical skills fit into common career trajectories. I observed that high-tech entrepreneurs often make technical or mixed technical-management skill transitions. High-tech entrepreneurs predominantly transitioned from technical staff positions or from junior manager and executive roles after first working in a technical staff positions in high-tech industry. The jump from technical staff roles is intuitive, as entrepreneurship in the high tech field often involves deep understanding or expertise of a technology, which is facilitated by direct training and work experience with a technology as a programmer, engineer, or analyst.

Moreover, entrepreneurship is a risky career transition in which most people consider the opportunity cost of pursuing new opportunities (Amit, Muller and Cockburn 1995, Reynolds 1987)—particularly where the opportunity cost is higher if their current compensation is lower. Thus ambitious and highly skilled lower-level technical staff have lower opportunity costs and might be disproportionally attracted to starting their own high tech venture. This tendency is likely exaggerated when there is a mismatch between the individual's skills and abilities and their job responsibilities. This mismatch tends to result in a poor wage (relative to skills) and in turn, encourages worker transition to entrepreneurship (Åstebro and Thompson 2011). Additionally, the transition from executive roles to entrepreneurship makes sense in light of prior research showing that the probability of creating a new venture is higher if the individual has more financial or social capital (Evans and Leighton 1989) or more transferable experience (Cooper, Woo and Dunkelberg 1989).

Although not as common as in the high tech industry, technical positions were fairly common among the career paths of finance entrepreneurs. This makes sense given the digital turn in finance, which increasingly involves elite analytical and programming skills needed to build sophisticated learning and trading algorithms. These individuals typically entered into entrepreneurship earlier in their careers, transitioning from technical staff or staff positions rather than from senior staff or senior management positions. The high compensation for senior personnel and executives in the finance industry makes risky transitions to entrepreneurship less attractive, the longer individuals work in the industry. Technical staff positions were less common along the career paths of entrepreneurs in other industries outside of high tech and finance.

Similar to the career paths to high tech entrepreneurs, I find that mixed skill transitions are common among many high tech executives and senior managers, where career paths included a mix of technical and management work experience. I find that many individuals reach the high-tech executive role from junior and senior management positions after first working at technical staff positions within the high-tech field. One possible explanation is that high-tech executives need more understanding of technology to facilitate managing the technical experts and divisions within the firm. This idea of the mixed skill transferability is reflected in Mark Hurd's advice to aspiring CEOs.

> "Don't worry about being CEO, worry about doing as many jobs as you can so that if you ever become CEO, when you're in the meeting with a bunch of people, you've done as many of their jobs as possible." - Mark Hurd, Chief Executive Officer of Oracle

In addition, some people enter the executive roles after working in different industries, acquiring some diversity of experiences. This is observed for both high tech and non-high tech executive roles, but multiple industry experience is especially common for non-high tech fields. Considering the common paths to executive positions in all industries, the skillset of executives seems to be transferable, as evidenced by the volume and industry-diversity of inter-industry executive-to-executive transitions. I also observed a clear "technical track" to executive positions, in which individuals transition from technical staff, to senior technical staff, to high tech executives. A closer look at the data reveals these tracks often lead to positions as Chief Technology Officer (CTO).

While the career paths to executive roles included large portion of inter-industry transitions, most paths to senior management include predominately intra-industry transitions. In high tech, I find some lateral inter-industry transitions from senior management positions in corporate and media, but many of these corporate and media senior managers had previously worked as junior managers in the high tech field and thus are returning high tech industry. Moreover, the high tech and finance industries are distinct from other industries in the number of individuals who work in technical staff positions along their career paths to senior management. One explanation is that technical experience is important to effectively managing technical projects, which I observe in the specific job titles and job descriptions of individuals following this mixed skill career path. For example, technical understanding can help project managers assess the difficulty of particular tasks and differentiate the abilities of technical employees working on a project, which is helpful in creating timelines and assigning teams.

Based the analysis, it is reasonable to suggest that the interaction of opportunity structures and skill portability are key explanatory factors for how/when (under what conditions) people transfer from one industry to another. As discussed above, the strong job growth in industries like high tech, education, and health services in the last few decades provided better opportunities for career advancement and better wages relative to stagnating industries. In addition to the relative and aggregate employment numbers in a given industry, structural changes in industries will impact individual career transitions via the creation and destruction of career opportunities. To take an obvious example, we have observed the fractionalization of particular industries, most notably media. While the media industry used to be more centralized, with distinguished firms/outlets entrusted with professional sourced news and information (e.g. NYT, Washington Post), the rise of social media has enabled more decentralized production of content to smaller target audiences. Social media platforms enable unprecedented levels of targeting by ever-increasingly specific personality/identity/taste characteristics. This fractionalization has enabled more opportunities for entrepreneurs launching media startups, which can chip away at the broader audience once commanded by larger media outlets. It also creates more capacity to find a niche audience and produce content that speaks to specific groups (groups based on ideology, politics, morality, personality etc.).

Career opportunities yielded by the relative growth of particular industries provides an insufficient explanation, because workers must have transferable skills to be able to capitalize on those opportunities. In the high tech industry, the findings suggest that technical skills and a mix of technical and management skills facilitate intra-industry, or inter-industry, transitions to entrepreneurship, executives, and senior managers. The results suggest that entrepreneurial and executive-level experience are more transferable between industries, while entry and staff-level skills are less transferable across industries. Thus, individuals in staff roles are more likely to make intra-industry transitions to more senior-level roles.

I find that individuals with certain transferable skills—notably technical, management, mixed, and boundary-spanning experience—are more likely to be in position to capitalize on job opportunities from differential growth across industries. Specifically, high-tech entrepreneurs tend to be "jacks of all trades" with more general-purpose skills that can be more readily transferred to more specific domains in other industries with high opportunity potential. Thus, people who develop skills in high-tech are more likely to make inter-industry transitions based on opportunity potential. This could explain trends such as tech entrepreneurs going into online, digital training programs (educational) and entertainment programs—essentially making a high-tech company using digital technologies to educate/entertain people. In short, the findings suggest that when an individual has portable skills and high opportunities in different industries, this individual is more likely to transition to different industry. Overall, I have discussed several insights regarding common career transitions of entrepreneurs, executives, and senior management. These insights can better inform managers during their decision making process, while in the recruitment and hiring process for new positions. For example, manager might be more willing to consider candidates transitioning from seemingly unrelated industries, or candidates with mixed skillsets that do not intuitively match a position's requirements. Conversely, these insights are helpful for career coaches, academic counselors, and individuals in the labor market (or about to enter the market) who are eager to understand the career paths that will improve the likelihood of reaching their career goals.

CONCLUSION

This paper analyzes 67,000 career profiles from a popular social networking platform. I build career trajectories (as network graphs) that provide insights on career paths of entrepreneurs, executives, and senior managers. In these career trajectory graphs, each node is a job consisting of an industry-level and seniority-level classification. Focusing on high-tech industry, I find that individuals with certain transferable skills — notably technical, management, mixed, and boundary-spanning experience — are more likely to be in position to capitalize on job opportunities across industries. Furthermore, I test these insights by developing and refining a supervised learning model for predicting individual career transitions of 10,000 individuals and achieve 48% accuracy for 204 job choices. Managerially, these insights can help in recruitment, career planning, job search and more.

While the analysis provided many insights useful for managers and labor market scholarship, there are some limitations. The prediction accuracy in testing the insights from the network approach to career trajectories gives us some confidence in the findings, but the prediction accuracy could be improved by considering multilayer neural networks or sequential pattern mining. Moreover, devising a procedure for correctly classifying 427,054 jobs into meaningful categories is a non-trivial task, thus there might be some errors in the industry classification. Those errors would propagate in the prediction process and likely be responsible for some reduction in the prediction rate. One way to evaluate and potentially improve the classification accuracy is using Mturk. I suggest both of these avenues for future work.

Chapter 2: Social Networks, Funding, and Regional Advantages in Technology Entrepreneurship

Economic factors, funding opportunities and social networks have influenced entrepreneurs' choice of their startup location. With increased penetration of digital technologies in startups, the traditional need for proximity to specific locations or large funding for infrastructure development have diminished. Digital entrepreneurs now pursue locations that provide more opportunities for funding and greater social support, and enable lower startup costs. In this paper, I use economic indicators made publicly available by the U.S. government, investment information from CrunchBase, and professional histories and network data from LinkedIn, to study regional and personal factors that influence digital entrepreneurs' location choice. These digital entrepreneurs have a choice to establish a startup in their current location or move to a different location. When relocating, entrepreneurs decide to create a startup immediately or delay it by a short duration (possibly to be more embedded in local environment). Analysis of 1,424 entrepreneurs, suggests that funding rounds per year play a significant and positive role in influencing startup creation and local social network proportion and tenure in location provide a stickiness to decision making and negatively influence entrepreneurs' decisions to relocate.

INTRODUCTION

Digital technologies have disrupted many industries by impacting the entire value chain, business models, and strategies of organizations (Bharadwaj et al. 2013, Rai and Tang 2014). However, these technologies have especially impacted digital entrepreneurship by reducing startup costs and giving entrepreneurs additional degree of freedom in their location choices for new ventures. Choice of location is especially important for digital entrepreneurs because attractive locations are likely to become more expensive as the demand for that location increases. This has been true for Silicon Valley that has gained a prominent position for digital entrepreneurship (Kotkin and Schill 2015) but is now losing the charm because of increasing costs of real-estate and talent.

Schumpeter (1942) places the entrepreneur at the center of the economic and technological growth. The literature shows that entrepreneurship is a key factor in moving technology from the laboratory to the market and the link between a country's economic prosperity and the creation of an economic future (Ács and Audretsch 2003, Glaeser, Rosenthal and Strange 2010). With the changing nature and requirements of startups in the current economy, this research seeks to understand the factors that influence the movement of digital entrepreneurs to high-tech regions. More specifically, I examine the factors that influence entrepreneurs' location choices to either move to a high-tech hub, remain in their current location, or move to a new location and work for a short while before creating a startup.

In the U.S., technology entrepreneurship is predominantly linked to a few technology clusters with regional advantage. A key factor in developing regional advantage and prosperity associated with technology hubs is retaining and attracting high-skill talent. Although the San Francisco Bay area is still the dominant region among technology clusters, Austin (TX) has long been one of the top U.S. cities for high tech growth, presiding over the strongest expansion in tech sector employment and among the highest growth rates in STEM employment (Kotkin and Schill 2015). Moreover, Austin also ranks highest on the Kauffman Foundation's Startup Activity Index, derived from number of new entrepreneurs, startup density, and percent of entrepreneurs starting companies because of perceived market opportunities (Morelix et al. 2015). More recently, Kauffman's Index points to cities like Los Angeles and Miami showing robust growth in startups and technology employment. However, despite widespread interest in entrepreneurship and the importance of entrepreneurs to the local and regional economy (Shane and Ulrich 2004), we have a relatively limited understanding of factors that influence entrepreneurs' decision to move to a new location to create a startup, which contributes to the heterogeneous economic and technological growth among major metropolitan areas.

This study adds to the literature that examines the role of both aggregated metropolitan economic indicators and individual-level factors that influence individual (re)location decisions (Dahl and Sorenson 2009, Figueiredo, Guimaraes and Woodward 2002). This paper analyzes an original and novel dataset of entrepreneur career paths with direct observation of personal connections to empirically model the location and entrepreneurial choice of individuals. The following section discusses the related background literature used to develop a formalized theory for the location choice of entrepreneurs.

BACKGROUND AND LITERATURE

Technology Clusters

A large body of scholarship explores the foundations of regional advantage and the transformation of regions through technology entrepreneurship and explains why some regions have prospered and others have not (Gibson and Butler 2013, Saxenian 1994, Saxenian 1999, Venkataraman 2004). Much of the extant literature is concerned with ecosystems of agglomeration including spin-offs and the regional clustering of firms (Fetters et al. 2010, Marshall 1920, Moore 1993, Porter 1990, Saxenian 1994, Schumpeter and Opie 1934). As noted by Engel (2015), the literature on clustering explains how areas specializing in an industry gain competitive advantages as a result of economies of scale, reduction of transaction costs, and capturing spillover demand (Krugman and Obstfeld 1997). However, this account falls short in explaining how highly innovative clusters support the continuous emergence of technology startups, many of which are not similar to the original business concentration of the cluster. Focusing on entrepreneurs' location choice can help develop a richer understanding of what retains and attracts entrepreneurs launching these new startups that fuel high-tech clusters.

Conceptualized by Saxenian (1994), innovation-centered business clusters are geographic concentrations of related companies focused on a scientific or technological knowledge base. Firms in the cluster share common physical and human capital needs and often conduct business with each other. The concept of an innovation-centered business cluster added a stronger explanatory framework to the constant emergence of new firms in high tech clusters than the original cluster literature. Saxenian juxtaposed two high-tech clusters, Silicon Valley and Route 128 in Boston and showed how Silicon Valley emerged as the model for an innovation-centered business cluster. Research on Silicon Valley as a model for high-tech regions is very robust. It has examined levels of growth, productivity and employment (Feldman 2000, Steiner 1998) financing of new ventures (Hellmann 2000, Wonglimpiyarat 2006), industrial clustering (Kenney and Von Burg 1999), and cloning Silicon Valley (Engstrom 1987, Rosenberg 2002). Literature on Austin, Texas (Fetters et al. 2010, Gibson and Butler 2013, Smilor, Gibson and Kozmetsky 1989) and Route 128 in Boston (Dorfman 1983) has also contributed to understanding innovation-centered business clusters, specifically offering the “technopolis wheel” as a framework for operationalizing key economic indicators powering regional hubs for technology innovation (see Figure 9) (Smilor, Gibson and Kozmetsky 1989).

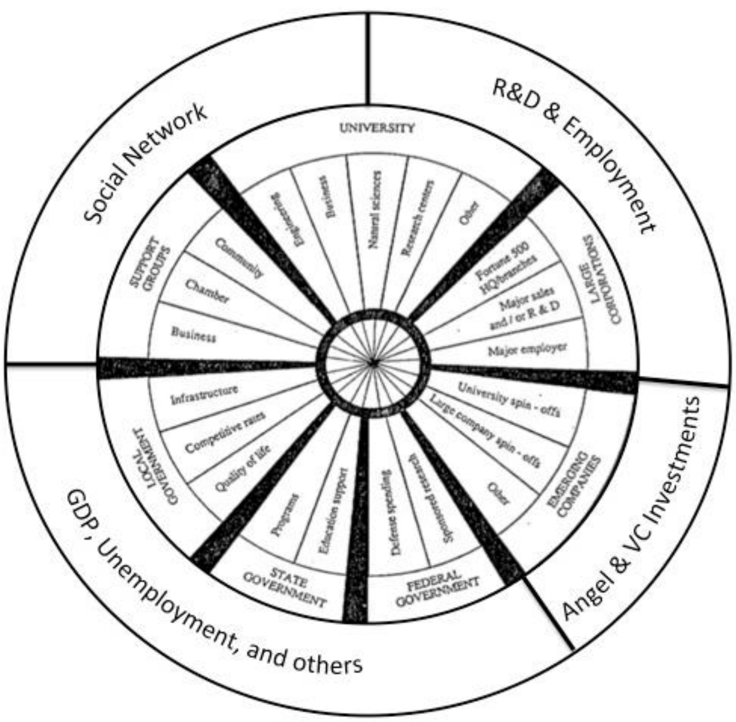


Figure 9: Measuring components of the technopolis wheel

The “technopolis wheel” (see Figure 9) shows the interaction of seven segments in the institutional make-up of innovation-centered business clusters. These segments include the research university, established technology companies, emerging technology companies, state and local governments, federal government and different support groups (Smilor, Gibson and Kozmetsky 1989). Past literature has established the importance of these institutional alliances (Etzkowitz and Leydesdorff 1997, Etzkowitz and Leydesdorff 2000, Powers 2004). This offers a clear framework for conceptualizing the economic and institutional factors influencing startup development and thus impacting entrepreneurs’ decisions. One can overlay several indicators on this framework to empirically measure the factors that influence entrepreneurship decisions regarding startup location, including employment and growth, investment availability, innovation, and the personal social network of the entrepreneur.

Social Networks and Embeddedness

In addition to the advantages of technology clusters and location-specific factors in the technopolis framework, individuals also value social connections and we sometimes underestimate the degree of influence social networks have on our career choices (Dahl and Sorenson 2010). We expect that social structures and networks influence an individual’s migrating pattern (Massey 1990). It has been shown that an individual's decision to move is influenced by localized concentration of their social network ties (Dahl and Sorenson 2010, Dahl and Sorenson 2012, White and Green 2010). Research has also shown that the size and strength of one’s local social network negatively impacts the individual’s propensity to move to a new location (Dahl and Sorenson 2010, Sjaastad 1962), even after controlling for wage and cost of living differentials between metropolitan areas (Michaelides 2011). Prior work also demonstrates that stronger interpersonal ties play a significant role in job search by unemployed individuals (Garg and Telang 2011) and shape information flow and knowledge diffusion among innovators (Ganco 2013, Singh 2005).

While many high performance individuals are motivated by and attracted to economic opportunity (Agarwal et al. 2004, Campbell et al. 2012), prior research indicates entrepreneurs have a propensity to start a company in the same locale where they previously worked because this choice enables them to use their existing local networks (Rogers 1995, Romanelli and Feldman 2004, Sorenson 2003). The literature shows that entrepreneurs tend to start their businesses in locations in which they have strong social ties or "deep roots", typically places where they have family and friends, yielding rich endowments of location embedded social capital (Dahl and Sorenson 2009, Dahl and Sorenson 2012, Katona and Morgan 1952, Michelacci and Silva 2007, Mueller and Morgan 1962). Moreover, with increasing penetration of online social networks, entrepreneurs can now more easily identify and connect with individuals that could provide support (business, social, or financial) to grow their startup. With the emergence of these online social networks and increased diffusion of information (Aral and Walker 2012, Garg, Smith and Telang 2011, Singh and Phelps 2013, Tambe and Hitt 2013), it is reasonable to expect that these multiple, online social connections will have an increased importance on decision-making and knowledge creation (Singh, Tan and Mookerjee 2011).

This study contributes to the literature on technology entrepreneurship by investigating the metropolitan and individual-level social network factors that influence how entrepreneurs select a location to start a company. Understanding why certain locations are better able to retain and attract digital entrepreneurs is a key component to explaining regional variation in entrepreneurial activity. Next, I formalize a theory for entrepreneurs' location choice and present testable hypotheses.

THEORY AND HYPOTHESIS DEVELOPMENT

Starting a new venture is risky due to the high level of uncertainty around the outcome (success). According to the U.S. Bureau of Labor Statistics (BLS), over 500,000 startups are created every month in United States1 and only 25% of those startups survive over time2.

---

[1] https://www.bls.gov/bdm/entrepreneurship/entrepreneurship.htm

[2] http://mashable.com/2014/01/30/startup-success-infographic/

Despite the uncertainty, entrepreneurs accept the risk and incur lost wages and other costs associated with running a startup because they expect a lucrative exit or significant profits (Peters 2009). At any given time-period an entrepreneur's period utility is driven by the difference in the net profit made by the new venture and the lost wages. During the early time periods, most startups generate little to no revenue and most entrepreneurs restrict their personal salaries below the market rate. Therefore, at the beginning, an entrepreneur is likely to have negative period utility because the lost wages and low net profits generated by the startup. As a result, an entrepreneur is likely to pursue funding opportunities or minimize costs to maximize the utility received from starting a company in location j at time t. Thus, startup location that lower the costs and maximize the probability of funding will then contribute to the selection of that location for a startup.

In addition, the growth and ubiquity of digital technologies has reduced the startup costs for entrepreneurs. Since technology startups usually have much lower infrastructure needs and remotely deployed resources (e.g., cloud-based computing) (Ross and Blumenstein 2015), entrepreneurs conceivably have more degrees of freedom in their location choice for new ventures (Heger, Veith and Rinawi 2011). Thus, a digital entrepreneur's location choice is driven by factors that influence the startup's ability to generating growth signals, acquire key resources, and reduce costs.

Growth signals for startups could include capital investment by external entities (e.g., VC firms, angel investors, etc.), patents, media coverage (Greenwood and Gopal Forthcoming), growth of customer base, and interpersonal or electronic word-of-mouth diffusion by their network (friends, employees, stakeholders, or consumers) (Aggarwal and Singh 2013, Aggarwal et al. 2012a, Aggarwal et al. 2012b, Greenwood and Gopal 2015, Susarla, Oh and Tan 2016). An entrepreneur's social network and local embeddedness are key resources that help a startup's development. Social connections can help reduce search costs as entrepreneurs filter information to access and secure vital resources (e.g., tacit technology knowledge, talent pools, supply and distribution chains, customers) (Ruef, Aldrich and Carter 2003, Sorenson and Waguespack

2006). Entrepreneurs acquire these local connections over time as they become more embedded in a location, thus creating stickiness for movement by imposing high transition costs to growing a venture in a new location where the entrepreneur has fewer connections and is less embedded.

Since costs vary for each metropolitan region, movement across regions is not costless, and location characteristics will adjust the period utility for each entrepreneur differently, I define three classes of entrepreneurs 1) entrepreneurs who are aware of other locations but decide to create a startup in their existing location , 2) entrepreneurs that have higher immediate utility to create a startup in new location, and 3) entrepreneurs that identify a new location for their startup but decide to embed themselves in that location before creating the new venture. Thus, I classify these three group of entrepreneurs (see Figure 10 below) as 1) entrepreneurs that don’t move and create a startup, 2) entrepreneurs that move and create a startup immediately, and 3) entrepreneurs that move and create a startup after a short delay (less than one year).

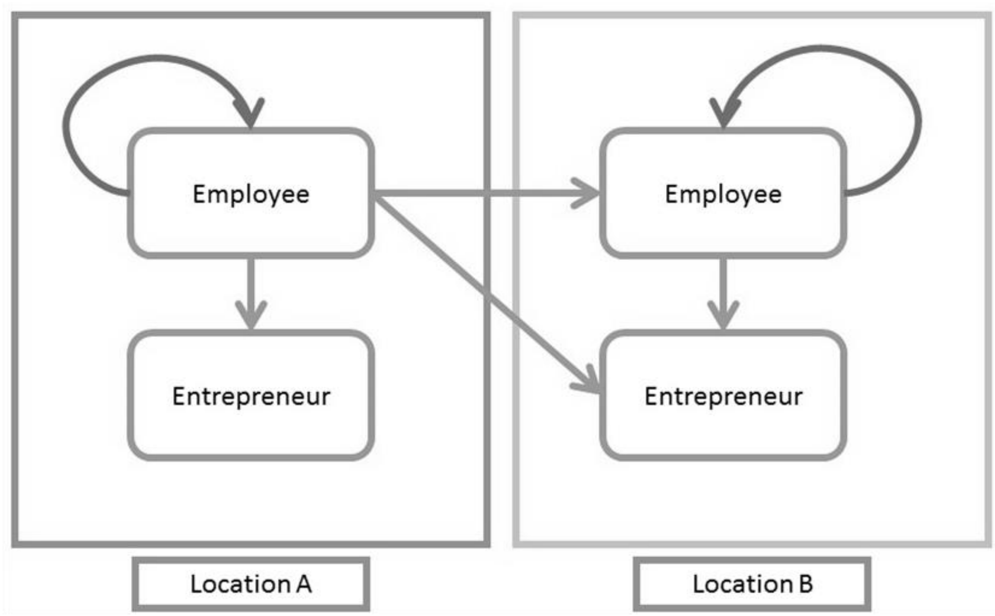


Figure 10: Entrepreneurs and Location Choices

For an entrepreneur's new venture, profit in a time period t is likely to be dependent on the profits or investments received in the previous time period because these market signals are likely to enhance the success of these startups (Conti, Thursby and Rothaermel 2010). For technology startups, capital investment from a prominent VC or Angel group is a valuable signal of the quality of a startup (Aggarwal, Kryscynski and Singh 2015). This "signaling function" of investment firms is important to startups' survival because working with a new venture is risky and many service providers (e.g., lawyers, recruiters, consultants) refuse to collaborate with a startup without this positive signal (Ferrary and Granovetter 2009). Moreover, prior research suggests that increased supply of venture capital in a location positively influences the number of startups launched (Samila and Sorenson 2011). Complementing this, anecdotal evidence from conversations with entrepreneurs suggests that digital entrepreneurs are largely driven by available funding opportunities in creating a startup. Thus, I expect that number of funding opportunities in a location are likely to influence the decision of an entrepreneur to select that location for creating technology startup.

Hypothesis 1a: Number of funding rounds in a location would influence potential entrepreneurs in creating a startup in that location and

Hypothesis 1b: Number of funding rounds in a location would attract potential entrepreneurs from different locations to create a startup in that location

In addition to funding, another important factor assumed to be important for a startup is innovation. Prior research on metropolitan areas have reported an association between higher patent rates and higher levels of innovation and productivity gains (Rothwell et al. 2013). Literature has also shown the importance of patents in creating geographically concentrated spin-off clusters (Butler and Gibson 2011). Thus, metropolitan areas with companies and research laboratories yielding more patents may potentially attract entrepreneurial talent with ambitions to leverage or license newly patented technologies in the future. New ventures based on sophisticated technology tend to launch near existing organization that developed the technology because effective use of the technology often requires active communication (Van den Bulte and

Moenaert 1998) and tacit knowledge that remains geographically concentrated and transferred through close social ties (Sorenson and Audia 2000). Furthermore, for technology startups, patents filed by a startup are also shown to provide a signal to investors, which is one of the primary motivations digital entrepreneurs give for seeking patent protection (Conti, Thursby and Rothaermel 2010, Sichelman 2015). As a result, I hypothesize that the number of patents in a region are likely to signal innovation culture of that region and attract potential entrepreneurs in selecting that location for their startup.

Hypothesis 2a: Number of patents in a location would influence potential entrepreneurs in creating a startup in that location and

Hypothesis 2b: Number of patents in a location would attract potential entrepreneurs from different locations to create a startup in that location

Digital entrepreneurs are likely to select locations for their startup where the local economic and labor market conditions are attractive for the growth. As noted earlier, I operationalize concepts from the technopolis wheel that measure key factors that may attract or retain entrepreneurial talent including metropolitan-level factors like the unemployment rate and local workforce (total employment). The association between unemployment and entrepreneurship is mixed in the literature and there is no concrete explanation for the relationship beyond underlying rigidities in the economy (Parker, 2009). When considering digital entrepreneurship, I expect that local talent becomes less important because the technology works could be distributed remotely across the globe. Thus, when a location has a larger workforce employed in different organization it is likely to discourage entrepreneurship because the local culture is favorable to employees. But, more intuitively, when a location has a larger unemployed labor it is likely to discourage entrepreneurship because the local community may not provide enough resources to develop and grow the startup. Still, the local economic conditions and unemployment rate could also influence the decisions of entrepreneurs to select a specific location. A location with thriving labor market may provide potentially attractive resources and customer base while a location with higher unemployment may discourage innovation. While not focal in the analysis, I include employment and unemployment rate as control variables in the model.

An entrepreneur's social network in a location is also an important factor in the development of their new venture. Working professionals with ambitions of launching their own venture become locally embedded over time as they acquire and maintain social and professional ties. This creates a stickiness to their current location because the entrepreneur would face friction in launching a startup in a new location where they are not locally embedded. Beyond the social and emotional utility generated by their existing connections, these local ties and knowledge is critical to reducing search costs for key resources for the new venture.

Launching a startup requires close relationships with mutual trust (Feldman 2000, Hite and Hesterly 2001, Porter 1998) between the entrepreneur and investors, boards of directors, financial and legal service providers, industry leaders (Krabel and Mueller 2009), and other entrepreneurs starting new ventures (Hsu 2006). These relationships are difficult to create quickly and are facilitated by consistent face-to-face interaction over time—thus relocating is costly in terms of developing new relationships in a foreign context (Figueiredo, Guimaraes and Woodward 2002). Further, research indicates that co-located social connections increase the odds of securing early funding from friends and family (Bygrave et al. 2003). Local social ties also influence funding opportunities from venture capitalists (Shane and Stuart 2002, Stuart and Sorenson 2003), in part because social ties offer a mechanism for investors to acquire information about entrepreneurs seeking to start new ventures and a means for entrepreneurs to establish a reputation (Amit, Glosten and Muller 1990, Shane and Cable 2002). Research has also shown that more socially embedded entrepreneurs have an easier time recruiting talent because prior relationships demonstrate reliability and increase employees' willingness to work for the entrepreneur (Ruef, Aldrich and Carter 2003, Sorenson and Waguespack 2006). Thus, I expect entrepreneurs to start companies in locations with a higher proportion of their social network ties, or tie-proportion.

Hypothesis 3a: Social stickiness: entrepreneurs' social network proportion in a location would encourage potential entrepreneurs in creating a startup in that location and

Hypothesis 3b: Social stickiness: entrepreneurs' social network proportion in a location would discourage potential entrepreneurs in creating a startup in a different location

Similarly, an entrepreneur's tenure in a location would then be an important factor influencing the location choice for the new venture, creating a stickiness for movement to a new location. Prior research also shows a strong relationship between time in a community and social attachment to a community (Dahl and Sorenson 2009). On average, the more time an entrepreneur spends in a place, the more socially attached they become to that community because they develop trust in community members and a personal connection to the history of a place (Hite 2005). Social attachment to place can also be an emotional affinity derived from social preferences to be near friends/family in a secure and enjoyable community (Dahl and Sorenson 2009). This is supported by research showing entrepreneurs tend to start companies in close proximity to location of birth (Michelacci and Silva 2007), and location of prior employment (Buenstorf and Klepper 2009, Figueiredo, Guimaraes and Woodward 2002, Parwada 2008). Thus, I expect the likelihood that an entrepreneur starts a company in a location increases in proportion to the time spent in that location.

Hypothesis 4a: Local stickiness: entrepreneurs' tenure in a location would encourage potential entrepreneurs in creating a startup in that location and

Hypothesis 4b: Local stickiness: entrepreneurs' tenure in a location would discourage potential entrepreneurs in creating a startup in a different location.

Overall, the hypotheses could be summarized in the Table 5 below:

Summary of Hypotheses

	Path 1	Path 2	Path 3
Social Stickiness	+ve (current location)	+ve (current location) -ve (past location)	
Local Stickiness	+ve (current location)	+ve (current location) -ve (past location)	
Funding	+ve (funding rounds)		
Innovation	+ve		

Table 5: Summary of Hypotheses

EMPIRICAL MODEL

To empirically validate the above hypotheses, I build on the prior theory in entrepreneurship and economics (Todaro 1969, Westlund and Bolton 2003, Woodward, Figueiredo and Guimaraes 2006) to propose that individual level utility received from entrepreneurship activity is:

$$U_{ij} = -c_{ij} - w_{ij} + \beta_1 X_{ij} + \beta_2 Z_j + \delta_i + \gamma_j + \varepsilon_{ij} \qquad (1)$$

Here c is the combination of cost incurred by entrepreneur i in a location j and w is monetary loss of income. X are the observable entrepreneur characteristics – including social network densities in location j, Z are the location specific time-varying characteristics that are represented in Technopolis – including the investments available in the region, and ε is the unobserved iid stochastic error assumed to have extreme value type I distribution. Prior research suggests that regional factors such as population, income and wealth, and employment within a region influence and individual's intent to become an entrepreneur (Kibler 2013). These metropolitan-level economic variables are included (Z) in the model.

Here the entrepreneur faces two decision choices 1) to continue working or start a new company or 2) to stay in existing location or move to a new location. I currently estimate and present the results for the conditional choice mixed model (Boskin 1974) and leave the possible nested nature of such decisions for future extension of this work. In addition, I add a location fixed effect to control for location specific, time-invariant unobservables such as local government infrastructure or universities. Thus, I estimate the following mixed logistic regression model:

$$D_{ijt}(X_{ijt}, Z_{jt-1}|f, j) = \beta_0 + \beta_1 X_{ijt} + \beta_2 Z_{jt-1} + \delta_i + \gamma_j + \varepsilon_{ij} \tag{2}$$

Where D is the observed binary decision of entrepreneur i to start a company in location j at time t that is a function of observable user (X) and location (Z) characteristics, which is conditional on user moving to a different location. Thus, I estimate three separate models with three different binary outcomes: 1) entrepreneur decides to start a company (vs. continue working) in the current location, 2) entrepreneur decides to move to a different location and immediately starts a company, and 3) entrepreneur decides to move to a different location (as employee) and start a company after a one-year delay (vs. continuing to work as employee beyond that time).[3]

DATA AND VARIABLE SPECIFICATION

To learn more about the aggregated metropolitan-level and individual social network factors underlying the geographic mobility of entrepreneurs, I focus on the within-country (United States) migration of entrepreneurs. I constructed a database of entrepreneurs' employment histories using individual LinkedIn profiles and startup investment data from CrunchBase—a self-reported database for startup funding and activity and the MoneyTree™ Report from PricewaterhouseCoopers and the National Venture Capital Association based on data provided by Thomson Reuters. The CrunchBase and PwC databases included company names of 41,615 startups that received at least one infusion of venture or angel capital between 1995 and 2014-Q1 (data collected 2014-Q3).

[3] The logit model is well-justified here because I model and interpret each outcome separately (independently). Individuals can choose to launch a startup multiple times in different time periods, and indeed some of the entrepreneurs in the database are serial entrepreneurs over their careers. Whether or not to launch a venture is a repeated, independent choice that individuals make at each job transition. Furthermore, I selected the logit model rather than the multinomial logit model (another valid option) because the logit model offers a more intelligible interpretation of the estimates.

I randomly sampled 2,000 startups from this investment database. Using LinkedIn public profiles, I identified the startup founder/co-founder of these startups. In cases of multiple co-founders, I only selected one co-founder so the individual entrepreneur database included one entrepreneur per startup. Of these 2000 randomly selected startups, I acquired the complete LinkedIn profile data for 1,424 entrepreneurs (352 of which founded 2 or more startups) while remaining 576 had incomplete profiles, mostly missing location data. These complete profile pages contained self-reported job histories and education including titles, dates, locations, as well as the entrepreneurs' skill endorsements. The analysis focuses on these 1,424 entrepreneurs.

I also acquired social network data from LinkedIn but since much of the online social networks are comprised of weak ties (De Meo et al. 2014), I used endorsement ties because they can provide a reasonable proxy for stronger ties in one's social network. A skill endorsement tie is established on LinkedIn when a member of an entrepreneur's first-degree network endorses him/her for a particular work-related skill or attribute (e.g., leadership, creativity, work ethic). These skill endorsements are generated voluntarily at any time by individuals in one's network. These endorsements are not solicited by the receiver and endorsements can be removed by either the giver or receiver at any time. The fact that an entrepreneur has accepted an endorsement, at the least, suggests some reasonable degree of familiarity with the endorser and willingness to be publicly associated with their contact on their home profile page. Although the specific motivation of each individual endorsement is well outside the scope of this analysis, in general it is reasonable to suggest endorsers aim to strengthen their connection perhaps hoping to receive reciprocal endorsements or to facilitate contact at a later date. Therefore, endorsement ties are expected to be stronger ties of social networks than generic connections. To further mitigate the risk of over- or under-estimating the role of local social networks I consider tie-proportion in a location for empirical analysis.

Next, I collected location-specific data for 68 large metropolitan statistical areas (MSAs). I geocoded (latitude/longitude coordinates) the current and past locations listed on LinkedIn profiles of the entrepreneurs and skill endorsement connections. I then collapsed all geocoded locations within 100 miles of a MSAs to the nearest MSA. I collected economic variables for the 68 MSAs using the Bureau of Labor Statistics (BLS) metropolitan-level databases. I used investment data from CrunchBase, a comprehensive self-reported database for startup funding and activity. For patent data at the metropolitan level, I used the Strumsky Patent Database (Strumsky 2014) that contains annual counts for patents granted by the US Patent and Trademark office between 1975 and 2013 (Bearman 1997).

Variable specifications

Individual-Level variables

In the model, graduate education is a binary indicator variable that has a value of one if the entrepreneur has a graduate degree. Tie-proportion measures the percentage of endorsement ties residing in a location. For each entrepreneur, this measure is simply the fraction of the number of endorsement ties in a given location divided by the total number of endorsement ties. I created a variable for an entrepreneur's "stickiness" to a location; I measure current location stickiness as the cumulative work experience in the current location. For entrepreneurs that change locations from their previous job and start a company (either immediately or after a short-term job), I measure previous location stickiness as the cumulative work experience in previous location.

MSA-level variables

Average funding averages the investment-funding amount per year for the 68 metropolitan areas. Total funding rounds count the number of funding rounds per year in each metropolitan area. Patents equal the total number of patents per year in a given metropolitan area.

To measure the economic strength of MSAs, I used several indicators of metro-performance. Unemployment rate is the percentage of people unemployed per year by metropolitan area. Employment is the number of employed persons in a metropolitan area. I also created two binary indicator variables to control for time. Recession has a value of 1 if an entrepreneur's job started in the U.S. recession between 2007-2009. Post-recession has a value 1 if an entrepreneur's' job started after the latest recession (2010-2014). Coding the variables in this way makes jobs started in the pre-recession period as the baseline. Table 6 presents descriptive statistics for the variables specified in the models.

Descriptive statistics (N = 7241)

Variables	mean	sd
Individual-level		
Tie-Proportion	0.36	0.279
Cumulative Tenure at Location of Last Job (Yrs)	6.00	5.740
Cumulative Work Experience (Yrs)	7.33	7.464
Metro-level		
Avg. Funding Per Year (in millions)(1-yr lag)	7.01	7.81
Funding-Rounds Per Year (1-yr lag)	303.14	537.01
Patents (in thousands)(1-yr lag)	1.86	2.64
Employment (in millions)(1-yr lag)	2.71	2.58
Unemployment Rate(1-yr lag)	6.82	2.30
Observations	7243	

Table 6: Descriptive Statistics

The 1,424 entrepreneurs in the dataset reported 7,241 jobs in their career, and 2,077 of those jobs were founder/co-founder jobs launching a startup[4]. Among these entrepreneurs, 55 percent did not move and founded a startup in their existing MSA, 31 percent moved and immediately founded a startup, and 15 percent moved and worked a short-term job before starting a company.

[4] The number of founding jobs is larger than the number of entrepreneurs because 352 entrepreneurs founded 2 or more startups.

Among entrepreneurs who migrated and started a company within the first year of moving to the new location, I find entrepreneur migration highly concentrated in a few metropolitan areas. As shown in Figure 11, 63 percent of relocating entrepreneurs moved to one of five metropolitan areas, the San Francisco Bay area, Austin, New York City, Los Angeles, and Boston. These top destinations for launching startups are consistent with past literature on technology innovation clusters. Not surprisingly, the San Francisco Bay area that includes Silicon Valley/San Jose was the top destination, attracting over a quarter (26 percent) of moving entrepreneurs. All of these metropolitan areas are also consistently reported in traditional media outlets as the top locations for entrepreneurs launching startups (Morelix et al. 2015).

Most of these top locations also have the most funding rounds for startups (see Figure 12). The San Francisco Bay area had 28 percent of all recorded funding rounds and far more rounds (15,407) than the rest of the locations, with New York City having the next highest (6,258) funding rounds. However, Austin, which attracted the second most entrepreneurs, was 10th and 13th respectively in terms of total funding rounds and total funding amount raised by metropolitan area.

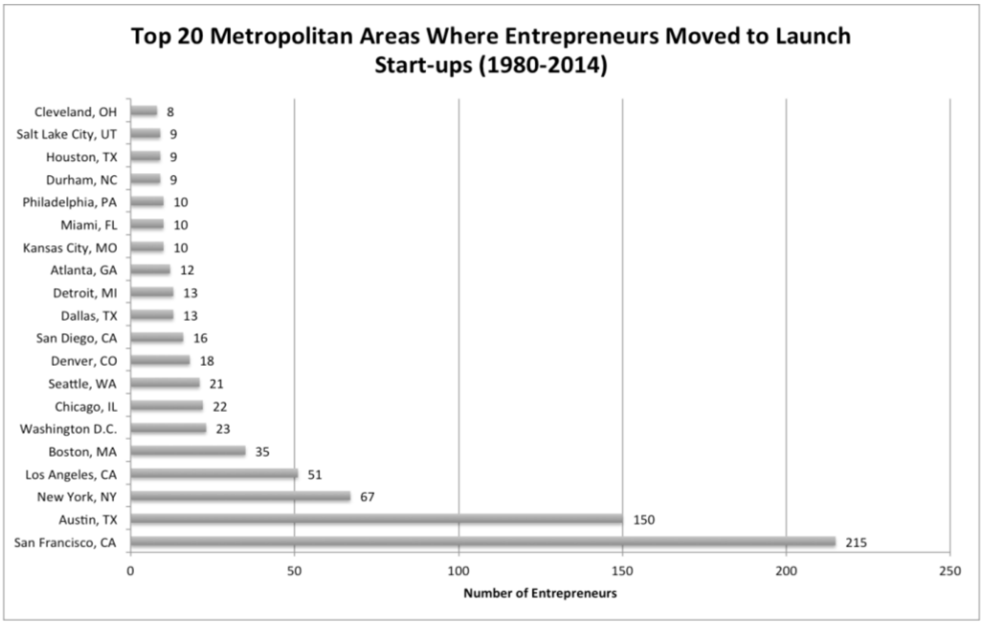


Figure 11: Target locations for entrepreneurs

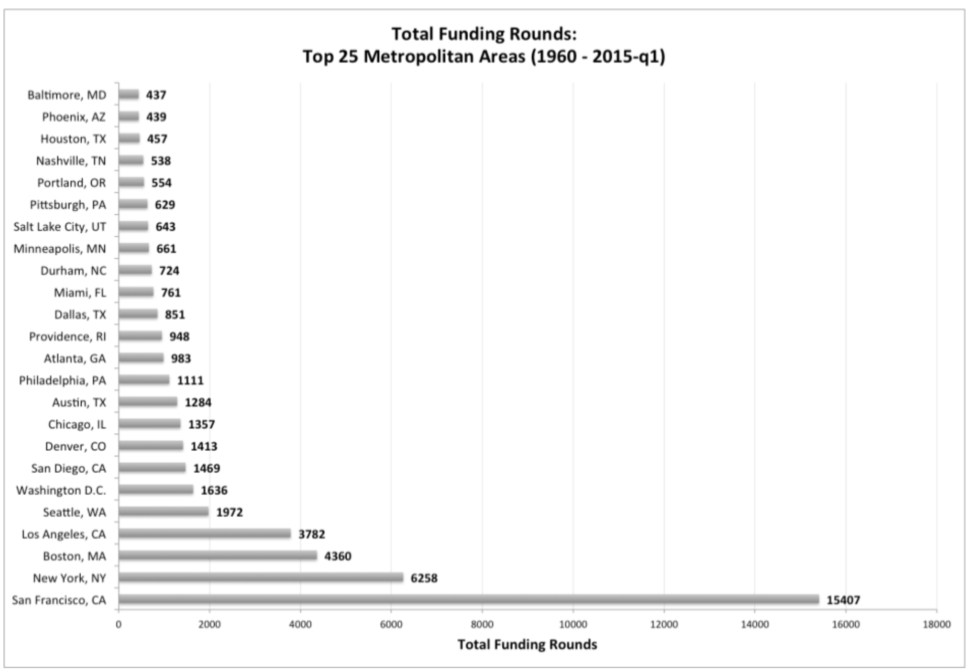


Figure 12: Startup funding rounds by location

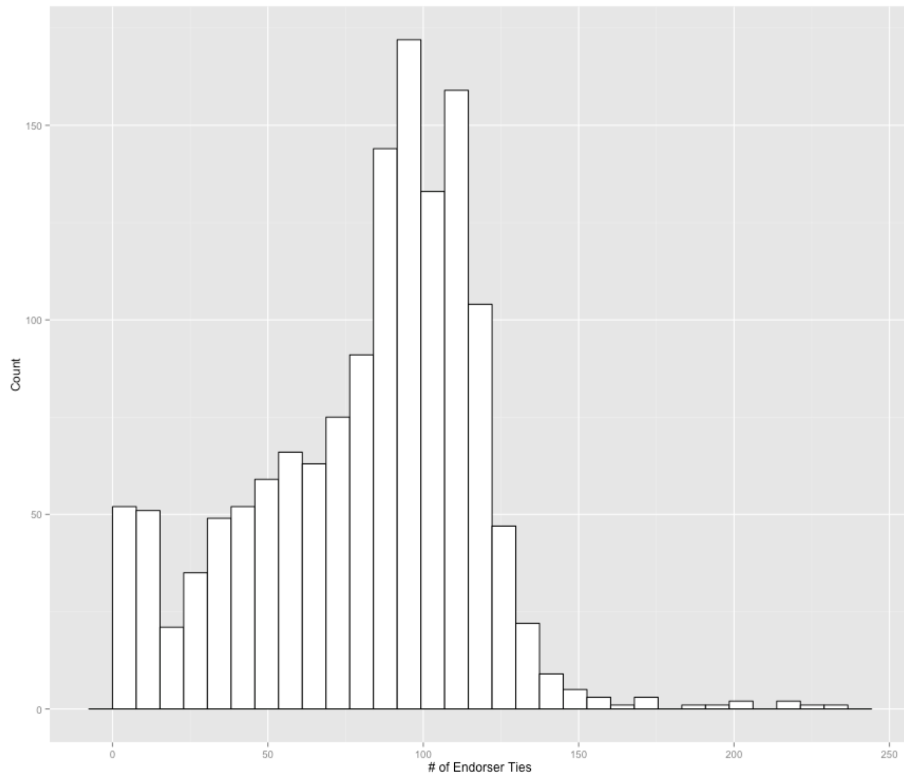


Figure 13: Distribution of entrepreneurs' endorsement ties

Looking at social network factors, the distribution of entrepreneurs' endorsement ties is shown in Figure 13. The median number of ties for entrepreneurs is 89 and the tie distribution is skewed right with few entrepreneurs having more than 130 social ties. Figure 14 shows top 15 pairwise location transitions among entrepreneurs. Consistent with popular press reporting on the top entrepreneurial hubs, the larger San Francisco Bay Area (Silicon Valley), Austin, and New York appear as top destinations for entrepreneurs who move and launch startups.

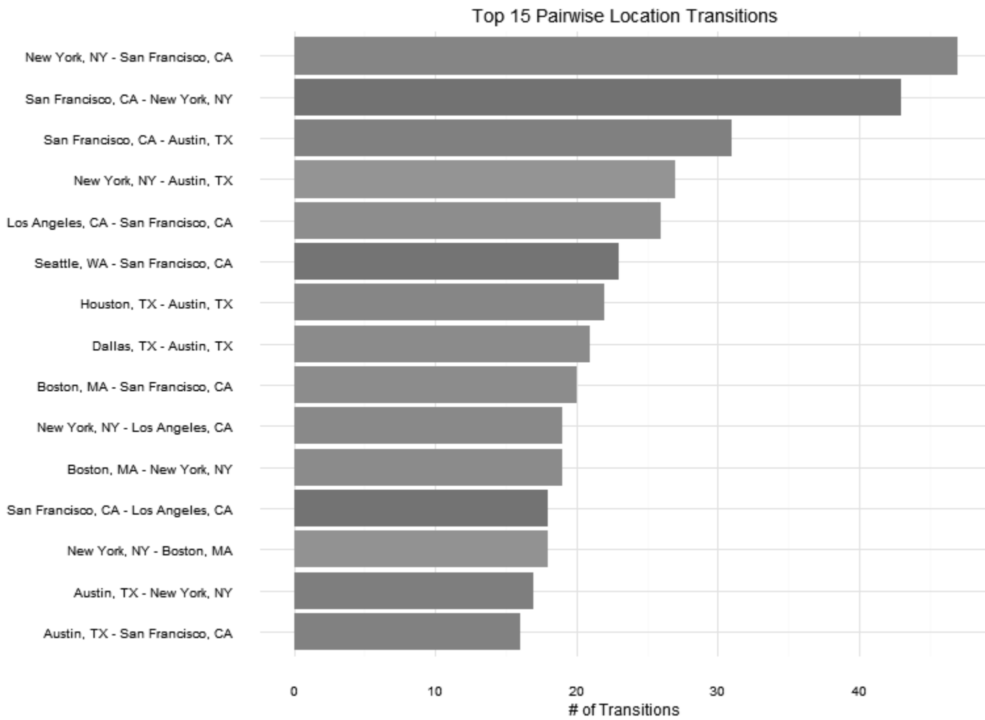


Figure 14: Top 15 Pairwise Location Transitions

RESULTS

Table 7 presents the estimated beta coefficients of logistic regressions. I report the odds ratios (exponentiated coefficients) to facilitate interpretation. The dependent variable in columns 1 and 2 is a binary indicator of whether or not the entrepreneur started a company in the same location. Both columns 1 and 2 are specified with random effects for entrepreneurs.[5] In columns 2, I introduce a metropolitan area fixed effect and remove the economic indicators.[6] In columns 3 and 4, the dependent variable is whether or not the entrepreneur moved to a different location and immediately started a company. The dependent variable for columns 5 and 6 is whether or not the entrepreneur moved to different location and started a company after a short delay (worked as an employee for a duration of one year or less before starting a company). The model specification is the same across all the models, except for the location stickiness variable. When

[5] I also specified the models with an individual fixed effect to account for individual-specific unobservables that might be correlated with the dependent variable, but the estimates did not significantly change.

[6] It is plausible that there might be other omitted metro-level variables correlated with the dependent variable, such as the number of research institutes, universities, or startups in a metropolitan area. The location fixed effect controls for these unobservables, thus reducing omitted variable bias.

entrepreneurs change locations, the stickiness variable measures the cumulative work experience in the previous location (prior to the startup location). For columns 3 and 4, this is the location of the previous job. For columns 5 and 6, this is the location of the job before the short-term job (because the short-term job is in the same location as the startup). In columns 1 and 2, the entrepreneur is not changing locations to launch the startup, so the stickiness measure is the cumulative work experience in the current location where the startup is launched (not including the duration of the founder job).

Logistic regression estimates for entrepreneur startups in same/different locations

	(1) Non-move & Founder	(2) Non-move & Founder	(3) Move & Immediately Founder	(4) Move & Immediately Founder	(5) Move & Other-Job, Then Founder	(6) Move & Other-Job, Then Founder
main		With Metro FE		With Metro FE		With Metro FE
Grad Degree	-0.141+	-0.218**	-0.0645	-0.0670	0.250+	0.244+
	(0.0811)	(0.0731)	(0.100)	(0.0899)	(0.139)	(0.129)
Cumulative Work Experience (Yrs)	-0.0711***	-0.0599***	0.0639***	0.0690***	0.0769***	0.0818***
	(0.00874)	(0.00752)	(0.00656)	(0.00612)	(0.00908)	(0.00804)
Tie-Proportion	0.895***	1.029***	-1.630***	-1.431***	0.614*	0.532*
	(0.153)	(0.142)	(0.229)	(0.207)	(0.279)	(0.267)
Cumulative Work Experience in Current Location	0.132*** (0.00919)	0.119*** (0.00770)				
Cumulative Work Experience in Previous Location			-0.0512*** (0.0114)	-0.0507*** (0.0102)	-0.119*** (0.0184)	-0.115*** (0.0173)
ln(Funding-Rounds Per Year)(1-yr lag)	0.0788* (0.0315)	0.268*** (0.0354)	0.0833* (0.0402)	0.248*** (0.0444)	0.306*** (0.0599)	0.444*** (0.0966)
ln(Avg. Funding Per Year)(1-yr lag)	0.0218	0.0239+	-0.0218	-0.0205	-0.0444	-0.0735
	(0.0140)	(0.0140)	(0.0202)	(0.0173)	(0.0329)	(0.0356)
ln(Number of Patents)(1-yr lag)	0.00235		0.00383		0.00825	
	(0.00211)		(0.00241)		(0.00367)	
Unemployment Rate(1-yr lag)	-0.0764*		0.0693		-0.156**	
	(0.0325)		(0.0405)		(0.0579)	
Employment (persons)	-1.13e-08		-6.96e-08**		-7.49e-08*	
	(1.56e-08)		(2.50e-08)		(3.43e-08)	
During Recession (2007-2009)	0.203		0.482+		-0.685+	
	(0.174)		(0.253)		(0.399)	
After Recession (2010-2014)	1.159***		0.654*		0.897**	
	(0.191)		(0.266)		(0.338)	
Constant	-3.110***	-2.561***	-2.945***	-2.824**	-3.787***	-4.364***
	(0.237)	(0.142)	(0.318)	(1.007)	(0.467)	(0.263)
Observations	5096	6955	5096	6929	5096	6572

Standard errors in parentheses
+ p < 0.10, * p < 0.05, ** p < 0.01, *** p < 0.001

Table 7: Logistic regression estimates for entrepreneur startups in same/different locations

The estimates for tie-proportion (in Table 7, columns 1 and 2) are positive and significant for entrepreneurs who start a company in their current location. This indicates that entrepreneurs are more likely to start a company in their present location if their tie-proportion in that location is high, suggesting that ties play an important role in supporting entrepreneurs thus supporting hypothesis H3a. Interpreting column 2 in Table 7, for a 0.1 increase in the tie-proportion in a location, ceteris paribus, the odds of an entrepreneur starting a company increase by a factor of 1.11 and this estimate is statistically significant ($p<0.001$).

The tie-proportion estimates are also significant for entrepreneurs changing locations and starting companies. If an entrepreneur's tie-proportion in a current metropolitan area is higher, the entrepreneur is less likely to move to a different location and start a company immediately thus supporting hypothesis H3b. If an entrepreneur's tie-proportion in a new metropolitan area is higher, I observe that entrepreneurs are more likely to start a company in the new location after a short duration working as employee thus supporting hypothesis H3a. Interpreting column 4 in Table 7, for a 0.1 increase in the tie-proportion in a location, the odds of an entrepreneur immediately starting a company after changing locations decrease by a factor of 0.87, holding all other variables constant and this estimate is statistically significant ($p<0.001$). Interpreting column 6 in Table 7, for a 0.1 increase in the tie-proportion in a new location, the odds of an entrepreneur starting a company in the new location after working for a short while increase by a factor of 1.05. This estimate is also statistically significant ($p<0.05$).

These estimates support my expectations that the role of social networks (tie-proportion in a current location) is an important factor when entrepreneurs are deciding where to start their company. Entrepreneurs that decide to move to a new location can capitalize on network ties after being in that location for some time and growing their social network. It takes time and effort to enrich professional ties. As social beings, personal and professional relationships take time to develop trust, needing repeated interactions producing experiences that enable evaluation of reputation and character. As these professional ties enhance over time, eventually they can be mobilized for resources that benefit both parties in some way. Having a delay between changing locations and starting a company—measured in this case as having a short-term job in the destination location before launching the startup—enables entrepreneurs to enrich their professional ties in the destination location, acquire additional connections, and use their network to mobilize resources (e.g., funding, expertise, talent) needed to start a company. A few initial connections in a new location may be instrumental in encouraging an entrepreneur to change location and possibly provide help with job transition, but it appears that developing a large network in that location is critical to launching the startup. This is intuitive from a network view because when a higher percentage of one's social network is comprised of local ties then the business opportunities one can "observe" is locally limited because of one's position in the social structure (Burt 2004).

Here, a plausible moderating factor is the metropolitan areas' entrepreneur ecosystem, which includes the organization of wealth, startup infrastructure in place, and the metropolitan areas' overall attitude toward startups. Locations with strong entrepreneurial ecosystems have formal and informal infrastructure that support networking among those with ambitions to launch, work for, or fund new startups. Ecosystems that facilitate social tie formation and enrichment among those in the startup community increase tie-proportion.

Cumulative time spent in a location, that is, "location stickiness" significantly influences entrepreneurs when choosing a startup location. The results show that the longer entrepreneurs remain in a location, the more likely they are to establish the startup in that location thus supporting hypothesis H4a. From Table 7 (model 2), I see that a one-year increase in cumulative time spent in a location increased the odds of starting a company in that location by 1.13 (statistically significant at 95% level). Additionally, from Table 7 (model 4), I see that a one-year increase in cumulative time in a location reduces the odds of starting a company in a different location by 0.96 in the move to a new location and start a company immediately scenario thus supporting hypothesis H4b. In the move to a new location, work as an employee for a short while and then start a company scenario, a one-year increase in cumulative time in a location reduces the chances of this happening by 0.89. Both estimates are statistically significant (p<0.001). These estimates correspond to my theoretical expectations suggesting some degree of geographic inertia or stickiness in which entrepreneurs' tend to grow more attached to location over time and therefore less likely to move elsewhere to start a company (Dahl and Sorenson 2012).

Next, I interpret the estimates for the metropolitan-level fixed effects, startup funding measures, and economic indicators.[7] All of the effects for the technopolis variables are lagged by one year because recent economic trends are most likely to influence entrepreneurs' movement decisions (i.e., it is unlikely entrepreneurs can gauge and immediately act on real time macroeconomic factors for the current year). Moreover, I specified alternative models with no lag, two-year lag, and three-year lag for the technopolis variables, and the estimates did not significantly change. The location fixed effect controls for location specific, time-invariant unobservables such as local government infrastructure or universities. Regarding entrepreneur's choice whether or not to launch a company, the fixed effect was positive and significant for several locations including: Atlanta, GA, Austin, TX, Boston, MA, Chicago, IL, Dallas, TX, Durham, NC, Los Angeles, CA, Miami, FL, New York, NY, Philadelphia, PA, San Diego, CA, San Francisco, CA, and Seattle, WA. This indicates that these locations by themselves have a propensity to retain and attract entrepreneurs that will go on to start companies.

I find an association between funding opportunities for startups in metropolitan areas and the movement patterns for entrepreneurs starting a company. The results indicate that locations' funding rounds per year have a positive and significant effect on whether or not an entrepreneur decides to change locations, work a job, and then start a company thus supporting hypotheses H1a and H1b. Interpreting model 2 in Table 7, a 10 percent increase in the number of funding

---

[7] As a robustness check, I also specified a model using the Milken Institute Best-Performing Cities Index, which includes a variety of measures of metro-performance including job, wage, and GDP growth and high-tech industry growth. This metro-performance index is a useful proxy for the economic indicators because including the economic indicators in the model with location fixed effects renders excessive multicollinearity (high VIF measures because the economic variables are highly correlated with location) and thus unintelligible estimates. Metro-performance index is a suitable proxy because it is positively correlated with patents and negatively correlated with the unemployment rate while removing multicollinearity. The beta estimates did not significantly change, reinforcing the results. I can provide these additional estimates in an appendix upon request.

rounds per year increases the odds that entrepreneurs will stay in the same locations and start their companies by a factor of 1.03, and this estimate is statistically significant ($p<0.001$). Interpreting model 4 in Table 7, a 10 percent increase in the number of funding rounds per year increases the odds ratio of the entrepreneur changing locations and starting a company immediately by 0.122. Interpreting model 6 in Table 7, a 10 percent increase in the number of funding rounds per year increases the odds ratio of the entrepreneur working a short-term job, and then starting a company by 0.149. Both estimates are statistically significant ($p<0.001$ and $p<0.001$, respectively).

The models also include a measure for the average funding amount per year, but the beta estimates were not statistically significant, except for model 2. A 10 percent increase in the average funding amount per year increases the odds ratio of entrepreneurs staying in the same locations and starting companies by 0.098, and this estimate is statistically significant ($p<0.1$). This was somewhat surprising because one would expect entrepreneurs to be driven by the funding amounts. Moreover, although average funding amount and number of funding rounds are not strongly correlated (which is why they are simultaneously included in the model specifications), I tried removing funding rounds and leaving average funding rounds in the specification, but the results did not significantly change. Based on my discussions with entrepreneurs and angel investors, I found that, in recent years, digital entrepreneurs usually seek small investments from angels and target larger amounts at a much later date. Thus during the early phase, they are likely to be attracted to a location that provides more opportunities for funding when compared to the amount of funding. To statistically test this, I further re-estimated the parameters with an interaction term with funding amount and a dummy for top ranked location (based on funding amount). The results sustained and I found no statistical significance on including a dummy for top 1 (Silicon Valley), top 2, top 3, top 5, or top 10 locations (based on funding amounts).

As a result, entrepreneurs believe that the larger number of funding rounds in a location is an indicator of more opportunity for securing funding for their startup. Additionally, because startups are typically funded in stages (Gompers and Lerner 2010), entrepreneurs likely associate more funding rounds in a location with a higher likelihood that their startup will continue to receive additional funding rounds beyond any initial investment capital. In short, entrepreneurs tend to gravitate towards places where they have more opportunity for funding.

Before introducing location fixed effects, I observe positive yet non-significant coefficients for the number of patents (in Table 7, models 1, 3, and 5), which is consistent with the prior work that documents positive and significant association between patents, productivity and innovation at the metropolitan level (Rothwell et al. 2013). Thus hypotheses H2a and H2b are partially supported in that patents play a positive role but are not significant in the analysis. This could be the case because technologically advanced firms may want to distance themselves from competitors (Alcacer and Chung 2007). I find a negative (and significant) association between the unemployment rate and entrepreneurs choosing to remain in the same location and start a company, and moving to a different location to launch a startup after working for a short duration. I also found a negative (and significant) association between the number of employed persons and relocating entrepreneurs starting a company immediately after changing locations and after working short-term. This large employment base could suggest that local culture is favorable to employees while at the same time when unemployment rate is high the local community may not provide enough resources to develop and grow a startup.

As explained above, I find a positive and significant influence of entrepreneur's tie-proportion on propensity to start a company in the same location as pre-entrepreneurship engagement. However, one might suggest that evolution of tie-proportion in a location be correlated with an individual's tenure in that location. While I do not have time series data on the evolution of social networks, I address this concern by testing the results by simulating the tie-proportion in a metropolitan area based on entrepreneurs' tenures in current and past locations. A well-documented finding in the literature is that relationships are more likely to develop between co-located persons. In many social contexts, the likelihood of any tie formation decreases rapidly as the physical distance separating two parties increases (Baker 1984, Bossard 1932, Kono et al.

1998a, Sorenson and Stuart 2001). At the dyadic level, co-location increases the likelihood of interaction between two parties and there is a tendency toward mutuality in relations over time because of the social pressure to reciprocate interactions (Gouldner 1960). Because tie-proportion is simply the connections in a location divided by the total connections in all locations, a dynamic conception of entrepreneurs' tie-proportion is a function of the tenure in current and past locations. Formally, this new measure of tie-proportion is:

$$td_{ij\tau} = \frac{n_{ij} * \left(\sum_{t\in[0,\tau]} t_{ij}\right) / \left(\sum_{t\in[0,T]} t_{ij}\right)}{\sum_j \left(n_{ij} * \left(\sum_{t\in[0,\tau]} t_{ij}\right) / \left(\sum_{t\in[0,T]} t_{ij}\right)\right)}$$

Here, td is the time varying tie-proportion of an individual, t is a dummy representing a unit of time spent in location j by individual i, n the observed number of ties of individual i in location j, and τ represents the time period in consideration. It is worth noting that the denominator of this tie-proportion also changes when an individual has a smaller number of connections in a location. Thus, I converted the static view of tie-proportion per location into a time varying dynamic tie-proportion panel. As shown in Table 8, the significance and valence of results hold with this test. The assumption is there is a linear correlation of tie-proportion evolution with tenure in location. I leave the possibility of a non-linear relationship between social connections and tenure for further investigation under a standalone research paper.

Logistic regression estimates for entrepreneur startups in same/different locations (with tie-proportion panel)

	(1) Non-move & Founder	(2) Non-move & Founder	(3) Move & Immediately Founder	(4) Move & Immediately Founder	(5) Move & Other-Job, Then Founder	(6) Move & Other-Job, Then Founder
main		With Metro FE		With Metro FE		With Metro FE
Grad Degree	-0.126	-0.201**	-0.0850	-0.0845	0.243+	0.231+
	(0.0802)	(0.0726)	(0.102)	(0.0913)	(0.140)	(0.130)
Cumulative Work Experience (Yrs)	-0.0528***	-0.0481***	0.0615***	0.0666***	0.0764***	0.0803***
	(0.00838)	(0.00733)	(0.00680)	(0.00632)	(0.00908)	(0.00804)
Tie-Proportion(prime)	1.791***	1.780***	-1.103***	-0.977***	0.441*	0.354+
	(0.175)	(0.147)	(0.166)	(0.150)	(0.221)	(0.207)
Cumulative Work Experience in Current Location	0.101***	0.0973***				
	(0.00918)	(0.00745)				
Cumulative Work Experience in Previous Location			-0.0443***	-0.0444***	-0.119***	-0.111***
			(0.0123)	(0.0110)	(0.0197)	(0.0178)
ln(Funding-Rounds Per Year)(1-yr lag)	0.0871**	0.261***	0.0789+	0.266***	0.301***	0.431***
	(0.0318)	(0.0354)	(0.0405)	(0.0470)	(0.0607)	(0.0967)
ln(Avg. Funding Per Year)(1-yr lag)	0.0167	0.00833	-0.0154	-0.0195	-0.0444	-0.0697
	(0.0149)	(0.0143)	(0.0214)	(0.0183)	(0.0328)	(0.0357)
ln(Number of Patents)(1-yr lag)	0.00144		0.00383		0.00817	
	(0.00215)		(0.00244)		(0.00366)	
Unemployment Rate(1-yr lag)	-0.0848*		0.0718		-0.164**	
	(0.0332)		(0.0419)		(0.0590)	
Employment (persons)	1.55e-09		-7.36e-08**		-6.81e-08*	
	(1.55e-08)		(2.57e-08)		(3.41e-08)	
During Recession (2007-2009)	0.0816		0.500+		-0.686+	
	(0.177)		(0.263)		(0.401)	
After Recession (2010-2014)	1.015***		0.718**		0.901**	
	(0.190)		(0.275)		(0.343)	
Constant	-3.848***	-3.227***	-3.005***	-2.808**	-3.752***	-4.257***
	(0.276)	(0.175)	(0.326)	(1.019)	(0.469)	(0.271)
Observations	4933	6665	4933	6648	4933	6225

Standard errors in parentheses
+ p < 0.10, * p < 0.05, ** p < 0.01, *** p < 0.001

Table 8: Logistic regression estimates for entrepreneur startups in same/different locations (with tie-proportion panel)

Additionally, I observe that entrepreneurs are less likely to return to a metropolitan area if their tenure in a new location increases (see Figures 15 and 16). The likelihood of moving back to an original location is a function of the number of years they have lived outside that metro area. As a result, individuals will have smaller local social networks in a new location during the initial year and have a high probability of moving back to any of the prior locations. When they start building social networks in new locations, the likelihood of them staying and starting a company becomes higher. This robustness check8 further supports the estimates of social network on entrepreneurship.

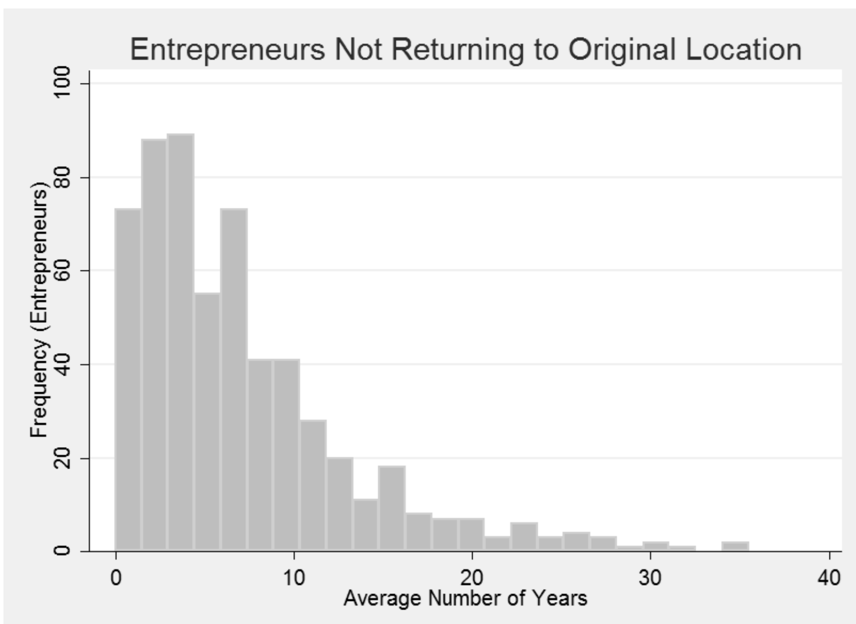


Figure 15: Histogram of tenure at different locations for entrepreneurs not returning to original location

[8] I ran several additional robustness checks which did not significantly impact the estimates or key findings. To list a few, I ran logistic regression models that incorporated the total number of endorsement ties in the specification. The estimates did not significantly change. I also ran models on a subset of single-founder entrepreneurs to control for bias from serial entrepreneurs. The estimates did not significantly change. If space is available, I can provide additional tables reporting these estimates upon request.

Figure 16: Histogram of tenure at different locations for entrepreneurs returning to original location

DISCUSSION

This paper makes several important contributions to the literature on technology entrepreneurship and regional advantage. This analysis is among the few that measures and examines the role of both aggregated metropolitan economic indicators and individual-level factors that influence individual (re)location decisions (Dahl and Sorenson 2009, Figueiredo, Guimaraes and Woodward 2002). As detailed above, prior work has focused on the influence of regional economic factors and agglomeration economies that yield high rates of spin-offs and subsequent clustering of innovative firms. Recognizing that the creation of a new venture is principally an individual decision made by a founding entrepreneur, the analysis uses an original dataset of entrepreneur career paths with direct observation of personal connections, in addition to key economic and investment factors, to model the location and entrepreneurial choice of individuals.

This analysis differs from and extends prior work in several important ways. I utilize rich data from a popular social networking platform to directly measure an individual's networks in particular locations and in turn evaluate the influence of social connections on the entrepreneur's decision where the launch the startup. Without access to recent data sources enabled by digital networking platforms, prior work relied on indirect proxy measurements for network proportion such as generic high school classmates (Dahl and Sorenson 2010), the physical distance between an entrepreneur's residential address and the addresses of their hometown, parents, and siblings (Dahl and Sorenson 2009).

In contrast, my analysis leverages a direct and clear measure of entrepreneurs professional and social network proportion in particular locations. Moreover, the data focuses on the location-choice decisions by founders of technology ventures that were founded in the prominent technology clusters like San Francisco Bay Area, Boston, Austin, and New York. Prior work investigated Danish founders of mostly non-tech companies in traditional industries like hospitality, food, business services, and construction. Moreover, this earlier work primarily conceptualized social networks as family and friend connections (Dahl and Sorenson 2009), which is perhaps more appropriate for successfully launching new non-tech businesses primarily serving local clientele. A broader measure of professional social networks is more appropriate for the investigation of technology ventures, which often require richer social capital with connections to technological expertise, tacit knowledge (Sorenson and Audia 2000), and more specialized resources (Ferrary and Granovetter 2009), which are less likely to be found in the narrower family-friends network.

The results presented here have significant managerial and policy implications. First, conceptual frameworks like the "technopolis" or entrepreneurship ecosystem have been heavily influential in recent decades among public officials and business leaders, shaping public policy and business investments in major American cities like Austin (Gibson and Butler 2013) and Boston as well as many international cities around the globe (Gibson and Butler 2011, Fetters et al. 2010, p. 120). Yet the data was not available to operationalize and measure the individual-level factors and key economic indicators that influence entrepreneur (re)location decisions, which is central to refueling and sustaining technology clusters. The empirical analysis is a novel investigation of an unmeasured and untested theoretical construct known as the "technopolis wheel" and the results identify factors that are critical for cultivating existing entrepreneurial talent and attracting outside individuals with entrepreneurial ambition.

Specifically, the findings indicate that an entrepreneur's decision to start a company in a specific location is partially driven by the number of funding rounds in that location. It was surprising that the amount of funding available in a location did not have a statistically significant impact on entrepreneurs' relocation choices prior to launching startups. Given that the number of funding rounds has a significantly positive impact in entrepreneur location choice, state and city policy makers might think about policies that encourage the organization of angel networks groups, which fund much more seed investment rounds relative to the large dollar capital infusions by VC firms. These policies might include financial and other regulatory incentives. This seems particularly relevant to declining industrial metropolitan areas with stagnating local economies, which are striving to encourage local entrepreneurship and retain local talent that is flowing to cities like the San Francisco Bay Area, Austin, Boston, and Seattle. Access to sufficient investment is widely perceived, in the entrepreneurial community, to be the dominant impediment to startup success. Thus, future studies should further test this association, perhaps exploring potential moderating factors that could establish indirect relationships.

Additionally, I see that social network proportion plays a strong role in keeping an individual in a location (stickiness) and plays a significant role in attracting the potential entrepreneur to a different location to begin startup operations. I also observe that distances for relocation are not significant predictors anymore. Policy implications of the findings suggest that entrepreneurial talent that is locally embedded is less likely to move elsewhere when starting a company. This suggests that activities and policies that promote social tie formation and local embeddedness might encourage entrepreneurs to remain in that location to launch their company, which will likely yield positive benefits for the local economy. For example, local government or local business managers/owners might consider sponsoring attractive social events (e.g., meetups, networking events, concerts/arts/culture) like SXSW, which facilitate interpersonal interaction and in turn promote social tie formation and potentially enhance entrepreneurial activity. Moreover, this suggests public and business information systems that facilitate communication and interaction among groups/organization with a local community are likely to promote positive spillover effects for the local economy.

Furthermore, the result showing the influence of social networks for entrepreneurs starting companies in a new location, shortly after moving there, suggests entrepreneurial talent might launch ventures in locations where expanding one’s network is easier and where there are lower barriers to accessing key resources through networked connections. For example, the entrepreneurial ecosystem in the San Francisco Bay area and New York City are notorious for the “gatekeeping” process to networking, which inhibit quick access to resources like new venture capital. In contrast, locations like Austin or Seattle are reported by entrepreneurs to have more decentralized resource networks, which facilitates access to financial and other key resources.

Over the last 5 decades we have seen Silicon Valley, Boston, New York, San Diego, and Austin attract increasing numbers of tech-entrepreneurs. Most of the extant research attributes this rise of startups to favorable economic conditions offered by each of the locations. This research dives deeper and considers entrepreneurs' characteristics and their social networks to investigate, at the micro-level, entrepreneurial and relocation decision-making. As more data becomes available, scholars should put quantitative measurement to the many qualitative narratives that have developed concerning technology entrepreneurship. This research takes the first step in identifying the role that social networks, investment, and economic indicators have on technology entrepreneurship. Nevertheless, future research can further refine this analysis to better understand the selection of a specific location over multiple choices that were not selected. This could enable a better understanding of the rise of selected entrepreneurial hubs in the country.

Chapter 3: Entrepreneurial Ecosystems and Developing Networks: Austin, Boston, Silicon Valley, and New York

This study investigates the entrepreneurial ecosystems of Silicon Valley, Austin, Boston, and New York, which have established themselves as innovation-centered business clusters and entrepreneurial "talent magnets". I examine the factors that influence start-up activity by analyzing entrepreneurs who (1) elect to remain in a region, (2) those that move to a different region to start a company, and (3) those that move to a region, enter an occupation, and then start a company. Following a brief overview of each region, I specify models testing the importance of investment funding, social network ties, education, cumulative work experience and other factors in entrepreneurs' location choice decisions. I find that entrepreneur network ties in Austin and Silicon Valley are an important factor in retaining potential entrepreneurs. I also find that the number of funding rounds per year, or frequency of funding opportunities, influences whether or not entrepreneurs move elsewhere to start a new venture.

INTRODUCTION

Regional advantage stems from the geographic concentration of innovative industries that constantly yield spin-offs that refuel the hub. In these regions, many scholars have explained how innovation and entrepreneurship is derived from the dynamic interactions of embedded agents in a complex web of networks (Ferrary and Granovetter 2009, Powell 1996, Powell et al. 2002). There are several theoretical frameworks that describe this geographic agglomeration of business activity including: business clusters (Porter 1990, Porter 1998), business ecosystem (Moore 1993, Moore 1996), and networks of innovation (Saxenian 1994) among others. All the frameworks stress the importance of spinoffs (Klepper 2010) and institutional support structures (Owen Smith and Powell 2005).

Building on the analysis in chapter 2 (above), I investigate the structural and cultural dynamics of four geographically distinct entrepreneurial ecosystems: Silicon Valley, Austin, Boston, and New York. Among entrepreneurs in the database collected and analyzed in this study (described in chapter 2 and below), these four locations were prominent destinations for launching technology startups (see Figure 14). Moreover, the literature on these regions have established these locations as technology innovation-centered business clusters and “talent magnets” with varying degrees of entrepreneurial success. Examined as 4 case studies, I investigate the selected ecosystems in three ways.

First, I detail the historical development of the entrepreneurial ecosystem in each location, with a particular focus on the institutional structures that helped develop the innovation-centered business cluster. Second, I specify the same empirical model (detailed in chapter 2) separately for each location. This analysis helps show whether there is location-specific variation in the influence of factors like social networks, funding opportunities, and economic factors on entrepreneur location choice. Third, I supplement the descriptive and empirical analyses with an analysis of interview data from technology entrepreneurs with experience in these locations. The interview responses explain how structural and cultural factors within ecosystems facilitate social capital formation. The findings describe the key structural factors entrepreneurs utilize in developing their network and highlight similarities and differences in the structural and cultural dynamics inherent to different ecosystems. Altogether, the analysis helps to explain some of the variation in the influence of social networks, funding opportunities, and economic factors on the location and entrepreneurial choice of individuals.

REGIONAL ADVANTAGE: INSTITUTIONS AND ECOSYSTEMS

The literature on regional advantage offers several explanations for why particular regions have prospered. The relationship between creative environments and creative regions can be traced to the analysis of regional clustering of firms (Marshall 1920, Porter 1990) and the innovation-centered business clusters (Dorfman 1983, Feldman 2000, Hellmann 2000, Kenney and Von Burg 1999, Saxenian 1994, Steiner 1998). Regional advantage stems from the geographic concentration of innovative industries that constantly yield spin-offs that refuel the hub. Geographically concentrated business clusters offer several advantages to new ventures. Clusters often specialize in a particular industry or technology and in turn attract key suppliers and labor talent to the area (Sorenson and Audia 2000). This provides new firms with lower cost access to material and human resources, providing competitive advantages that stem from economies of scale, reduction of transaction costs, and capturing spillover demand (Krugman and Obstfeld 1997, Porter 1990).

Research on high technology regions increasingly uses institutional theory as a guiding framework to help to explain entrepreneurial success (Foss and Gibson 2015). The institutionalist view recognizes these clusters develop robust networks of institutional support corresponding to the cluster's industry focus. Institutional structures that are important to regional advantage include universities, incubators and business accelerators, investments groups (e.g., angel networks, venture capital), large established enterprises, and legal and financial service organizations. In Boston, Owen-Smith and Powell (2004) document how various public and private institutions were deeply embedded in an inter-organizational network of formal and informal relations, which encouraged information spillover and helped fuel the "Route 128" biotechnology business cluster. In an important study, Smilor, Gibson and Kozmetsky (1989) developed the conceptual framework of the technopolis wheel (see Figure 17), which emphasized the key importance of academic, business, and government sectors and concentrated on how new institutional alliances could drive strategy and tactics of technology-based economic development.

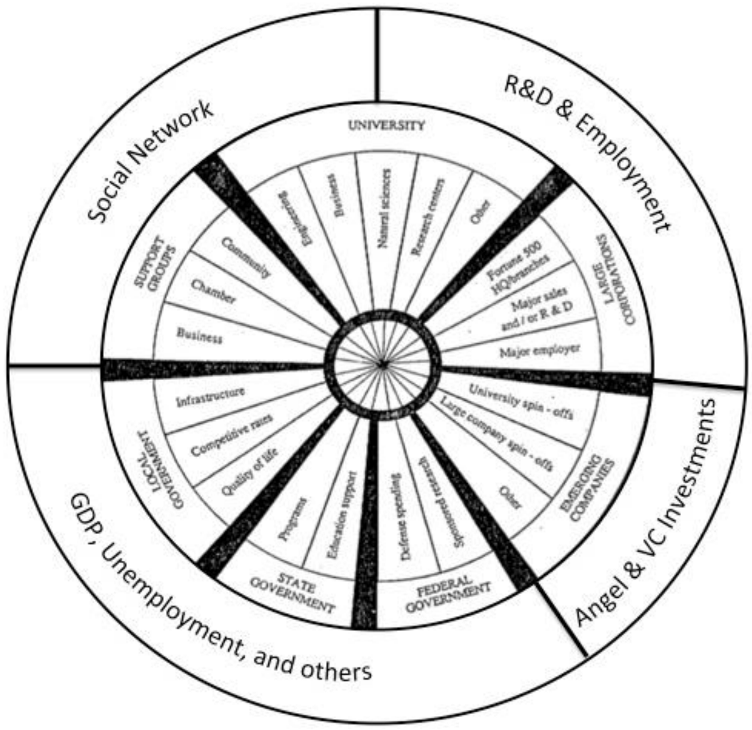


Figure 17: Measuring components of the technopolis wheel

Borrowing from ecology, Moore (1993) conceptualized this agglomeration of interconnected firms as a business ecosystem in which a variety of organizations coevolve around an innovation. Moore (1996) also stressed the idea that these geographic clusters are a magnet for talented people and interfirm collaboration alongside competition. These forces contributed to the diffusion of best practices throughout the ecosystem. These creative environments, which allow for competitive strategy, enhance interpersonal relationships, are often characterized by periods of relative stability and incremental change punctuated by major technological shifts that yield rapid changes (Scott 2014). Over time, technological breakthroughs displace prior innovations in waves of creative destruction (Schumpeter 1942). While few organizations can adapt and survive, healthy ecosystems yield new institutional networks that coevolve around the new frontier of innovation. In this view, entrepreneurs launch new ventures more frequently in these locations because these ecosystems allow individuals to accumulate the knowledge, social ties, and confidence necessary to mobilize resources for launching and sustaining a new venture. Thus, higher founding rates, not lower failure rates, sustain agglomerations (Sorenson and Audia 2000).

In the U.S., Silicon Valley, Boston, and Austin are three geographically concentrated innovation ecosystems that have yielded the most technology ventures. There is a large body of literature on each location (Butler 2010, Etzkowitz and Dzisah 2008, Kozmetsky, Gill and Smilor 1985, Owen Smith and Powell 2005, Powell et al. 2002, Saxenian 1994, Smilor, Gibson and Kozmetsky 1989). However, this literature does not investigate regional variation in the social, economic, and structural factors that influence entrepreneurs' location choice decisions. Research has noted that the key to developing regional economies lies not only in the development of institutional structures, but also the attraction of entrepreneurs and entrepreneurial talent to those regions (Florida 2005).

Building on this prior work, this chapter focuses on four case studies and investigates institutional structures and other individual and metropolitan-level factors that shape the location choice of entrepreneurs in each region. The next section provides some background on development of the entrepreneurial ecosystem in Silicon Valley, Austin, Boston, and New York City.

ENTREPRENEURIAL ECOSYSTEMS: METRO BACKGROUNDS

San Francisco Bay Area (Silicon Valley)

For the last several decades, Silicon Valley and the greater San Francisco Bay area has been the "800-pound gorilla" of innovation-centered business clusters and technology startups. Silicon Valley is the unquestionable global hub of entrepreneurship and innovation in a full spectrum of industries including software, information technology, Internet, social media, and biotechnology. Silicon Valley is a highly-concentrated cluster of technology firms, research institutions (e.g., Stanford, UC Berkeley), and venture capital and angel investment firms. In 2015, total venture capital investment for the greater Silicon Valley region reached $24.5 billion ($11.13 billion in Silicon Valley, and $13.34 billion in San Francisco), which is 42% of the total U.S. venture capital investment (Joint Venture Silicon Valley, 2016). Software investments comprise more than half (52%) of all Silicon Valley 2015 VC funding while smaller proportions went into other industries like biotechnology (13%), IT services (6%), and industrial/energy (5%). In 2014, total angel investment for the greater Silicon Valley region was $4.1 billion (roughly $1.8 billion in Silicon Valley, and $2.3 billion in San Francisco) (Joint Venture Silicon Valley, 2016).

Many prior studies detail the origins and development of the innovation-fueled business ecosystem in Silicon Valley (Castilla et al. 2000, Saxenian 1994). The Silicon Valley ecosystem successfully capitalized on each new wave of creative destruction initiated by each successive technological innovation (Henton and Held 2013, Schumpeter 1942). Although important to each regional cluster, spin-off firms are particularly important to understanding regional advantage in Silicon Valley (Saxenian 1994). In the 1950s, rapid growth in the semiconductor industry started in Silicon Valley with Shockley Semiconductor Laboratories (founded in 1956). Shockley Labs started attracting scientific talent, including many leading academics from STEM fields like engineering, math, and physics and their top graduate students. Fairchild Semiconductor was the key spin-off (founded in 1957).

The concentration of scientific and engineering talent in Fairchild eventually yielded many spin-offs including Intel, Advanced Micro Devices, and National Semiconductor. The invention of microprocessors at Intel in 1971 paved the way for the next technological wave in personal computers (1970s and 1980s). Bolstered by the concentration of talent, support industries, venture capital, and a culture that praised creative risk-taking (Saxenian 1994), newly developed personal computer companies (e.g., Apple and Hewlett-Packard) made computers a home commodity. The proliferation of personal computers in every home made the Internet and World Wide Web possible. This helped spawn the next wave of spin-off firms based on the Internet and information technology (e.g., Netscape and Cisco). In turn, Internet and information technology companies fueled rapid growth in software and computer-related employment, which further helped the Silicon Valley retain and attract ambitious and entrepreneurial talent.

Finally, this wave fueled the current wave of spin-offs in Internet and social media (e.g. Google, Facebook, Twitter, Airbnb, Uber). Silicon Valley ecosystem also supports starts biotechnology (e.g., 23andMe) and clean-technology (e.g., Tesla). Throughout this process, the spin-offs founded the new ventures near the parent organization (for the economic and social benefits discussed above) (see Sorenson and Audia 2000), which further attracted key resources like talent, support industries, and venture capital. Strong regional growth in Silicon Valley (in 2015, 4.3% employment growth rate and 3.6% unemployment rate) has led to a geographic expansion from the region's core in Santa Clara County (e.g., Palo Alto, Cupertino, San Jose) to adjacent parts of San Mateo, Alameda and Santa Cruz counties (e.g., San Francisco, Fremont, Gilroy). This expanded area covers 1,845 sq. miles and, in 2015, reported a large, diverse population of 3 million with strong foreign immigration (net +14,338) (Joint Venture Silicon Valley, 2016).

Beyond the concentration of resources, Saxenian (1994) emphasized the role of an innovative risk-taking culture in Silicon Valley as well as the critical role of research universities. Venture capital firms (VCs) in Silicon Valley had distinct financing objectives that strongly encouraged aggressive risk-taking (Saxenian 1994). Venture capital and angel networks are important to innovation clusters because they finance most new technology ventures and facilitate interactions and the creation of new ties between key players in the entrepreneur ecosystem. In Silicon Valley, VCs are central to the innovation clusters because they fund most successful new ventures (Ferrary and Granovetter 2009).

Austin, Texas

Austin is the capital of Texas and home to The University of Texas at Austin, and other private and public colleges and universities. Historically, employment opportunities in Austin revolved around the state government, colleges and universities, and small private firms. In contrast to the emergence of the high-tech business cluster in Silicon Valley, the Austin technology cluster was more the consequence of strategically planning. The transformation of Austin into a technology hub for innovation and entrepreneurship began with the vision of George Kozmetsky, who created a strategy to transform the city into a high-tech region to augment opportunities in other parts of the state mostly centered on the oil and gas industry. Kozmetsky created the Institute for Constructive Capitalism (IC^2), and its laboratory the Austin Technology Incubator, to be institutional catalysts for transforming Austin into an innovation-centered business cluster. One of the first companies in the Austin Technology Incubator was Pencom Software, which was admitted in 1989. Since its inception, IC^2 has launched over 150 companies, raised over $750 million dollars in investor funds for member companies, created initial public offerings, and had many companies acquired (Butler 2010).

Smilor, Gibson and Kozmetsky (1989) developed the technopolis wheel framework to explain the emergence of the high-tech cluster in Austin (see Figure 17). The technopolis wheel is composed of distinct institutional spokes including major research universities (e.g., UT Austin), technology companies and spin-offs (e.g., Tracor), federal, state, and local government, and support groups (e.g., angel networks, chamber of commerce). The institutional resources can be in place, but the cluster does not self-assemble. In this framework, networks of key influencers embedded in each institutional segment interact with other key influencers to form important institutional alliances, which in turn promoted the high-tech economic development of the Austin cluster (Smilor et al. 1989, Powers 2004). Austin's ecosystem changed quickly as the technopolis framework helped spur partnerships with the chamber of commerce, wealthy investors, industry, and universities/research laboratories. A Harvard-Business case study of the Austin technopolis model reported that this introduced a paradigm of technology-driven economic development driven by interlocking relationships between academia, business and government (Butler 2010).

In the 1990s Austin was one of the hubs for high-tech firms. The early business face of Austin, Dell Computers (whom Kozmetsky helped to mentor as Chairman of the Board). Other companies included Motorola, IBM, Applied Materials and Tracor (an early company founded as early as 1955). Kozmetsky's technopolis was given a boost in 1983 when Austin won a very competitive national competition that included over 50 localities, to bring the Microelectronics and Computer Technology Corporation (MCC) to the city (Smilor, Gibson and Kozmetsky 1989). Today, many of the Fortune 500 companies that are located in Austin include Apple, ARM holdings, eBay, Cisco, General Motors, Google, Intel, Texas Instruments, 3M, and Oracle Corporation. During the past few decades, Austin has produced firms like National Instruments, Dell Computers, Whole foods, Evolutionary Technologies, FreeScale (originally Metrowerks), and Golfsmith. Other homegrown companies include Uship, HotSchedules, Golden Frog, Alchemy, and Glofish. Austin is also celebrated for its lively culture—nicknamed the Live Music Capital of the World and home to Austin City Limits and SXSW Music Festival.

Today the Austin ranks highest on the Kauffman Foundation's Startup Activity Index, derived from the number of new entrepreneurs, startup density, and percent of entrepreneurs starting companies because of perceived market opportunities (Morelix et al. 2015). There is robust institutional support for startups in the Austin ecosystem. As of June 2017, I identified 39 entrepreneurial support "spaces" (e.g., incubators, accelerators, and co-working spaces) in greater Austin. From 2005 to 2016, thirteen "incubators" and 25 co-working spaces were launched in Austin. The culture, structure, amenities, and impact of these recently established entities has yet to be determined, but they have clearly provided increased visibility and support for Austin entrepreneurs. In 2015, angel network investors in greater Austin invested over $13 million in 43 companies (Central Texas Angel Network 2016). Venture capitalists infused $740 million in 99 Austin-area companies in 2015, far outpacing larger Texas cities like Dallas ($214 million) and Houston ($160 million) (MoneyTreeTM Report from PricewaterhouseCoopers and the National Venture Capital Association based on data provided by Thomson Reuters).

Boston

The greater Boston area (including Cambridge) has a robust technology startup ecosystem and central to one the largest geographic agglomerations of biotechnology firms in the world. In 2015, venture capitalists invested in 486 VC deals totaling $6.7 billion, which is roughly 5.3% of global VC investment (PitchBook 2016). In Boston, biotechnology is the largest sector of VC investment, receiving $2.9 billion in 91 biotechnology startups, second only to Silicon Valley and vastly outpaces all other regions. Software is the second largest sector with 160 Boston-based software startups receiving $1.6 billion in VC funding. While Silicon Valley slightly edges Boston in aggregate VC investment, Boston has an unparalleled concentration of elite public and private research institutions, including research universities (e.g., Harvard, MIT, Tufts, Northeastern), research hospitals (Brigham and Women's, Massachusetts General), medical research institutes (Dana Farber Cancer Center), and international leaders in the Human Genome Project (Whitehead Institute for Biomedical Research). Boston is also the R&D headquarters for major multinational pharmaceutical firms (e.g., Pfizer, Novartis) and Amgen (the largest biotech firm in annual sales).

Prior research traces the origins of Boston's biotech startup boom to the late 1970s and early 1980s with the founding of two major biotech pharmaceutical ventures, Biogen and Genzyme. Both firms were founded by leading scientists from nearby universities, which sparked other researchers and academics to launch their own startups. Largely fueled by public research funding, the Boston area eventually developed a robust venture capital sector during the 1990s, which further fueled the number of new biotech startups (Powell et al. 2002). To get a sense of the diverse and rich biotech ecosystem in Boston, between 1988 and 1999, Owen-Smith and Powell (2004) report that greater Boston had a total of 57 independent biotech firms, 19 public research organizations, and

37 venture capital firms. These organizations were deeply embedded through a dense network of formal and informal relationships (Owen-Smith and Powell 2004).

Other research contends that the strong public research presence in the Boston ecosystem has left an institutional imprint on Boston-based biotech firms. Owen Smith and Powell (2005) document how Boston-based biotech companies often focus their R&D on orphan medicines and therapeutic treatments for well-known patient groups. In contrast, R&D at Silicon Valley biotech firms often swing for “home-runs”, that is, pioneering first-ever medicines aimed at large global markets.

New York

With a population of 22,000,000 New York City (NYC) is the largest metropolis in the US. NYC has historically thrived on competition, innovative ideas, diversity, resilience, and determination, which make it a breeding ground for entrepreneurial activity (Stringer 2012). The high-tech industry’s young, creative talent is attracted to NYC because of the education and career opportunities, ethnic diversity, creative and entertainment industries, and NYC’s distinct urban lifestyle.

One key advantage of NYC’s technology industry is its cultural and ethnic diversity. The continued influx of skilled immigrants is important to expanding the talent base sought by high-tech firms. A 2013 report from the Office of the State of New York Comptroller showed that immigrants played a significant role in the high tech economy. Immigrants were employed in over one-third of many of the high-playing technology jobs (e.g., computer systems design, software publishing, and data processing and hosting services) (DiNapoli and Bleiwas 2014). Forty percent of the city’s tech employees are women and a fifth are people of color. Part of the reason New York has more diverse tech workers is because the companies in NYC offer a wide range of technology jobs. Many non-American startups use NYC as their American or North American headquarters, bringing in talented workers with international perspectives.

As of late 2013, NYC was home to 6,970 high-tech firms and high-tech employment was one of the fastest growing industries (DiNapoli and Bleiwas 2014). More than half of the high-tech sector jobs in NYC (56,000 jobs) were related to designing, managing and operating computer systems and digital media (such as Internet publishing and broadcasting). While software accounted for only 2 percent of high-tech jobs, it had the fastest rate of growth (58 percent). In addition, new digital and mobile technologies bolstered new ventures in NYC's advertising, publishing, media, design and entertainment industries (Bloomberg Technology Summit, 2013).

In NYC, the public and private sectors have launched many initiatives to help support entrepreneurship and the emerging high-tech industry by nurturing a skilled workforce. In 2011, Cornell University and Technion (Israel Institute of Technology) made significant infrastructure investments towards expanding their applied sciences and engineering campuses based on a land grant on Roosevelt Island. In another initiative, New York University (NYU), the City of New York, and several large tech firms partnered to launch NYU's Center for Urban Science and Progress (NYU CUSP)—a research center and graduate school focused on leveraging "big data" for creative enterprises and addressing major urban problems around the globe (Kickul and Mulloth 2015).

In another public-private partnership, the Polytechnic Institute (NYU Poly) and the New York City Economic Development Corporation (NYCEDC) worked together to launch several initiatives geared towards supporting local technology entrepreneurship. For example, the Varick Street Incubator provides affordable office space and business supplies/services in prime real estate in lower Manhattan. Other initiatives include the

NYC Accelerator, the DUMBO Incubator, and most recently a Clean Technology Entrepreneur Center. Moreover, Columbia University established the Institute for Data Sciences and Engineering in Morningside Heights and Carnegie Mellon University invested in an Integrative Media Program at the Brooklyn Navy Yard (Kickul and Mulloth 2015).

Furthermore, with its proximity to Wall Street and a growing venture capital community, NYC-based technology firms have access to large and diverse funding opportunities. In 2013, venture capital firms invested $1.3 billion in 222 high-tech companies in the NYC metropolitan region, according to the MoneyTree Report PricewaterhouseCoopers and the National Venture Capital Association, with Thomson Reuters' data. This ranked third among the nation's regions, following Silicon Valley and New England. Since the end of the last recession, high-tech venture capital investment in the NYC metropolitan region has doubled, growing at the same rate as in Silicon Valley and more than twice the rate of growth in New England. However, despite a population roughly eight times as large as San Francisco and being the global financial hub for the world's largest banks, NYC tech firms raised just 5 percent of the VC funds while Silicon Valley area companies received roughly 15 percent of the world's venture capital.

SOCIAL CAPITAL FORMATION IN ENTREPRENEURIAL ECOSYSTEMS

The analysis in this chapter focuses on the subset of entrepreneurs who started companies in at least one of four major technology startup hubs (Austin, Silicon Valley, Boston, New York) to learn more about the metropolitan and individual-level factors influencing the geographic movement of entrepreneurs. In addition to modeling factors that influence entrepreneurs' location choice in each of the four case study locations, I also analyze interview data collected from technology entrepreneurs. Entrepreneurs' launching new ventures have particular needs such as a technically skilled labor force, technological expertise, financial capital, and specialized legal or accounting support (Ferrary and Granovetter 2009, Kenney and Von Burg 1999). In addition to having a concentrated supply of these resources, I expect more robust entrepreneurial ecosystems will have structures that facilitate interaction and networking among entrepreneurs and key resources. I investigate the role these structures play in entrepreneurs' social capital formation, and how the role of these structures may vary based on the regional ecosystem.

Social Capital

Although important to individuals at all types of organizations, social capital is a foundational theoretical concept in entrepreneurship (Sorenson and Rogan 2014) and critical to the creation and development of new ventures. The three main theorists on the subject—Bourdieu, Coleman, and, Lin—define social capital in somewhat different ways, but they all conceive it as the resources embedded in social relations of individuals or groups (Bourdieu 1986:241-258; Coleman 1988:98-104; Lin 2001:29). They also all argued that four types of resources constitute social capital: information, the influence that networks have over people, the social credentials that networks can convert, and the personal/social value that supports mental health. Arguably most appropriate in the context of entrepreneurship, this chapter takes Lin's definition of social capital as the "resources embedded in a social structure that are accessed and/or mobilized in purposive actions." (Lin 2001:29). This definition stresses not only the purposive but also the rational nature of investments in social capital, mainly the capacity to utilize resources in one's network. In this way, social capital is flexible enough to constitute various entrepreneurship-related resources (e.g., funding, strategic advice, technology expertise, legal and accounting support etc.).

Entrepreneurs build social capital by creating and maintaining network ties. Social capital is particularly vital to entrepreneurs because it enables them to locate, access, and mobilize key resources (Davidsson and Honig 2003) such as financial capital (Hallen and Eisenhardt 2012, Shane and Cable 2002), talent, mentors, advisors and board members, and emotional support. Having more network ties reduces new ventures' liabilities of newness and smallness (Hite and Hesterly 2001) and increases the likelihood of survival from hostile external shocks (Venkataraman and Van de Ven 1998). Prior work also shows a positive association between social capital and firm performance (Baum, Calabrese and Silverman 2000), venture growth (Maurer and Ebers 2006, Vissa and Chacar 2009), and opportunity recognition and innovation (Cooper and Park 2008, Tsai and Ghoshal 1998, Uzzi 1997). Most studies have focused on the consequences of social capital, meaning outcomes derived from the structure of the networks in which individuals are embedded (Stam, Arzlanian and Elfring 2014). However, from both a theoretical and practical view, it is important to address the general question: how do entrepreneurs build social capital in these ecosystems?

Structures Facilitating Social Capital Formation

How do entrepreneurs build network ties to access key resources? To address this question, I conceptualize social capital formation as the interaction of network structure and process. The interaction consists of two concepts: 1) through what structures/entities (e.g., persons, organizations, groups, communities) do the entrepreneurs locate/access/mobilize a resource, and 2) what actions/behaviors do the entrepreneurs perform in creating/managing network ties that enable them to locate/access/mobilize a resource. The first concept focuses on the network structures that facilitate contact between the entrepreneurs and other individuals (resources). The second concept details the networking process, referring to the networking actions or "behavioral repertoires" utilized to create and manage interpersonal ties (Vissa 2012). In a future study, I will analyze the networking process of entrepreneurs in ecosystem. This chapter focuses the analysis on interview responses that describe the structures within ecosystems that were supportive in the entrepreneurs' networking activity and social capital formation.

DATA AND METHODS

Data Sources and Collection

For the empirical analysis, I constructed a database of entrepreneurs' employment histories using individual LinkedIn profiles and startup investment data from the MoneyTree™ Report from PricewaterhouseCoopers and the National Venture Capital Association based on data provided by Thomson Reuters. I randomly sampled startups based on historical startup investment data by region from PwC (1,765 startups). Of these startups, I selected only nascent entrepreneurs (551) that started a company in Austin, Silicon Valley, Boston, or New York (the four largest locations). Using LinkedIn public profiles, I identified the startup founders/co-founders of these startups and accessed the complete LinkedIn profile web pages for these startups. The profiles pages contained self-reported education and job histories including titles, dates, locations, as well as the entrepreneurs' endorsement network. I standardized the self-reported job locations by geocoding and mapping onto metropolitan statistical areas (MSAs).

I selected 68 large MSAs and then collapsed all geocoded locations (latitude/longitude coordinates) listed by entrepreneurs and endorsers to the nearest metropolitan area within 100 miles. I used aggregate city-level investment data from

CrunchBase, a comprehensive self-reported database for startup funding and activity, to compute the MSA-level investment information. For patent data at the metropolitan level, I used the Strumsky Patent Database (Strumsky 2014) that contains annual counts for patents granted by the US Patent and Trademark office between 1975 and 2013 (Bearman 1997).

I used LinkedIn endorsements rather than generic LinkedIn connections to measure the entrepreneurs' social networks. An endorsement tie is established on LinkedIn when a member of an entrepreneur's network endorses him/her for a professional/technical skill or attribute (e.g., leadership, creativity, technology). With increasing number of connections on online social networks that are dominantly comprised of weak-ties (De Meo et al. 2014), it is important for empirical analysis to consider ties that are likely to establish causal outcomes. These endorsements are voluntarily made by individuals in one's network and suggest some reasonable degree of familiarity with the endorser. Therefore, endorsement ties are expected to be stronger ties when compared to a generic LinkedIn connection in an online social network. Furthermore, I collected LinkedIn public profile of all individuals who endorsed the entrepreneurs in the dataset.

Variable specifications

Individual-Level variables

I use three individual level variables in the analysis 1) education, 2) local tie-proportion, and 3) location stickiness. Graduate education is a binary indicator variable that has a value of one if the entrepreneur has a graduate degree. Tie-proportion measures the percentage of endorsement ties in the location of current job. For each entrepreneur, this measure is simply the ratio of the number of endorsement ties in a given location divided by the total number of endorsement ties. I measure current location stickiness as the cumulative work experience in the current location. For entrepreneurs that change locations from their previous job and start a company (either immediately or after a short-term job (duration less than 1 year), I measure previous location stickiness as the cumulative work experience in previous location.

Metro-level variables

Average funding averages the investment-funding amount per year for the 68 metropolitan areas. Total funding rounds count the number of funding rounds per year in each metropolitan area. Patents equal the total number of patents per year in a given metropolitan area. Table 9 presents descriptive statistics for the variables specified in the models.

Descriptive statistics for Nascent Entrepreneurs (total N = 551)

	Austin		Boston		Silicon Valley		New York	
Variables	mean	sd	mean	sd	mean	sd	mean	sd
Individual-level								
Tie-Proportion	0.40	0.28	0.35	0.25	0.39	0.27	0.38	0.26
Cumulative Tenure at Location of Last Job (Yrs)	6.46	5.94	5.42	5.41	6.28	6.15	5.02	4.92
Cumulative Work Experience (Yrs)	8.32	7.98	6.94	7.15	7.33	7.43	6.00	6.06
Metro-level								
Funding-Rounds Per Year (1-yr lag)	101.65	177.78	287.55	323.66	794.84	828.89	407.29	410.21
Avg. Funding Per Year ($-millions) (1-yr lag)	6.57	7.26	7.94	5.01	7.91	5.79	8.30	6.47
Patents(1-yr lag)	2912.22	2382.54	5241.99	3988.24	1035.94	1835.28	874.32	2012.95
entrepreneurs	160		46		248		97	
Graduate Degree	76		23		141		45	
Total jobs	763		197		1063		461	

Table 9: Descriptive Statistics for Nascent Entrepreneurs

Among the 975 nascent entrepreneurs in the dataset, 551 launched a startup in one of the four major technology startup hubs (Austin, Silicon Valley, Boston, New York). The 551 entrepreneurs in the analysis reported 2,484 jobs in their career. Among these entrepreneur jobs, 56 percent did not move and founded a startup in their existing MSA, 30 percent moved and immediately founded a startup, and 14 percent moved and worked a short-term job before starting a company.

Empirical Specification

Using the same dataset of entrepreneurs as the analysis in chapter 2 (above), I separate the entrepreneurs who founded their startup in one of the four regions: Silicon Valley, Austin, Boston, and New York. For entrepreneurs in each location, I estimate the following mixed logit model[9]:

$$D_{ijt}(X_{ijt}, Z_{jt-1}|f, j) = \beta_0 + \beta_1 X_{ijt} + \beta_2 Z_{jt-1} + \delta_i + \gamma_j + \varepsilon_{ij} \qquad (2)$$

Where D is the observed binary decision of entrepreneur i to start a company in location j at time t that is a function of observable user (X) and location (Z) characteristics, which is conditional on user moving to a different location. Thus, I estimate three separate models with three different binary outcomes: 1) entrepreneur decides to start a company (vs. continue working) in the current location, 2) entrepreneur decides to move to a different location and immediately starts a company, and 3) entrepreneur decides to move to a different location (as employee) and start a company after a one-year delay (vs. continuing to work as employee beyond that time).

As a robustness check, I also specified models using the Milken Institute Best-Performing Cities Index[10], which includes a variety of measures of metro-performance including job, wage, and GDP growth and high-tech industry growth. This metro-performance index is a useful proxy for the overall economic strength of the greater metropolitan area. Metro-performance index is a suitable proxy because it is positively correlated with patents and negatively correlated with the unemployment rate while

[9] The logit model is well-justified here because I model and interpret each outcome separately (independently). Individuals can choose to launch a startup multiple times in different time periods, and indeed some of the entrepreneurs in the database are serial entrepreneurs over their careers. Whether or not to launch a venture is a repeated, independent choice that individuals make at each job transition. Furthermore, I selected the logit model rather than the multinomial logit model (another valid option) because the logit model offers a more intelligible interpretation of the estimates.

[10] http://www.milkeninstitute.org/publications/view/897

removing multicollinearity. The beta estimates did not significantly change, reinforcing the results.

Interview Data

The interview data was collected as part of a larger research project on digital and mobile media entrepreneurship.[11] One research objective of the project aimed to better understand networking activity and social capital formation among digital technology entrepreneurs. As a member of the research team, we conducted 45 semi-structured, in-depth interviews with technology entrepreneurs, collected between 2015 and 2017. The interviews lasted 1-2 hours (on average) and included a section of questions about the role of social networks and network activity in the process of launching a startup. We used purposive sampling to attain variation in entrepreneur perspective, considering venture location, development stage (early stage to more mature ventures), type of business (creative content, professional or technical services etc.), genre (e.g., gaming, education, entertainment, health, productivity, social, etc.).

Table 10 reports the geographic and demographic characteristics of the entrepreneurs that were interviewed. Due to availability and limited travel funds, over half of the entrepreneurs were from Austin, but many were located in other metropolitan areas such as Silicon Valley/San Francisco, New York City, Chicago, Washington D.C., and St. Louis. Moreover, many of the entrepreneurs had lived in multiple locations and were quite familiar with the entrepreneurial ecosystems in each location. Pseudonyms of entrepreneurs and their ventures are used throughout to assure privacy and confidentiality.

[11] Dr. Wenhong Chen is the principle investigator (PI) on the project.

Demographic Distribution of Entrepreneur Interviewees (N=45)

		Count	Percentage
Location	Austin	31	69%
	Silicon Valley/SF Bay Area	5	11%
	Washington DC	3	7%
	New York City	3	7%
	Chicago	2	4%
	St. Louis	1	2%
Gender	Male	34	76%
	Female	11	24%
Race/Ethnicity	White	35	78%
	Asian	6	13%
	Black	3	7%
	Latino	1	2%
Age	30-39	20	44%
	40+	16	36%
	20-29	9	20%
Total		45	100%

Table 10: Demographic Distribution of Entrepreneur Interviewees (N=45)

Based on analysis of all 45 interviews, the responses captured important descriptions about structural and cultural factors of local ecosystems and how they relate to entrepreneur social capital formation. The entrepreneur responses were particularly valuable in comparing the structures and culture within different ecosystems. In turn, I analyze the entrepreneur interviews and report findings on the important structural elements of the ecosystems more generally, as well as location-specific characteristics of the ecosystems for the selected case studies (Austin, San Francisco, Boston, New York).

RESULTS AND DISCUSSION

Table 11 presents the estimated beta coefficients of logistic regressions for entrepreneurs in Austin, Silicon Valley, Boston, and New York who decided to remain in the same location and start a company. To facilitate the interpretations in the text below, I report the odds ratios (exponentiated coefficients). For each of the four locations in the analysis, I separated entrepreneurs by where they launched a startup and fit a separate logistic regression model. I picked separate logit models because each entrepreneur in the group could be intrinsically different and thus the coefficients could have different significance. The dependent variable in columns 1-4 is a binary indicator of entrepreneur starting a company in the same location.

The tie-proportion estimates for entrepreneurs in Austin and Silicon Valley (in Table 11, models 1 and 3) are positive and significant for entrepreneurs who start a company in their current location. For persons in Austin and Silicon Valley, this indicates that entrepreneurs are more likely to start a company in their present location if their tie-proportion in that location is high, suggesting that ties play an important role in supporting entrepreneurs. Interpreting the model for Austin, for a 0.1 increase in the tie-proportion in a location, ceteris paribus, the odds of an entrepreneur starting a company increase by a factor of 1.20 and this estimate is statistically significant ($p<0.001$). Interpreting the model for Silicon Valley, for a 0.1 increase in the tie-proportion in a location, ceteris paribus, the odds of an entrepreneur starting a company increase by a factor of 1.11 and this estimate is statistically significant ($p<0.001$). This suggests that social networks in Austin and Silicon Valley are an important factor in retaining potential entrepreneurs to start a company in the near future. Entrepreneurs embedded or "plugged-in" the Austin and Silicon Valley ecosystems are more likely to stay in that location when launching a startup. The estimates for entrepreneurs in Boston and New York were not statistically significant.

Logistic regression estimates for entrepreneurs who started companies in same location (Non-Movers) by Region

	Dependent variable:			
	Non-move and Founder			
	(1) Austin	(2) Boston	(3) S.V.	(4) New York
Grad Degree	-0.137	-0.481	-0.141	0.038
	(0.253)	(0.501)	(0.202)	(0.320)
Cumulative Work Experience (Yrs)	-0.013	-0.046	-0.072***	-0.110***
	(0.021)	(0.047)	(0.022)	(0.043)
Tie-Proportion (current location)	1.789***	-1.320	1.042**	1.072
	(0.552)	(1.042)	(0.432)	(0.681)
Cumulative Work Experience in Current Location	0.087***	0.142***	0.115***	0.193***
	(0.025)	(0.055)	(0.024)	(0.045)
ln(Funding-Rounds Per Year)(1-yr lag)	0.697***	0.170	0.486***	0.052
	(0.170)	(0.176)	(0.088)	(0.150)
ln(Avg. Funding Per Year)(1-yr lag)	-0.067	1.212	-0.014	0.119
	(0.063)	(0.814)	(0.057)	(0.088)
ln(Number of Patents)(1-yr lag)	0.311	1.037***	-0.389**	-1.158**
	(0.193)	(0.351)	(0.187)	(0.511)
Constant	-7.601***	-30.437**	-2.708**	1.214
	(1.621)	(14.188)	(1.284)	(3.351)
Economic Controls (metro-performance index)	yes	yes	yes	yes
Observations	709	178	922	414
Note: (Odds Ratios reported in text)	*p<0.1; **p<0.05; ***p<0.01			

Table 11: Logistic regression estimates for entrepreneurs who started companies in same location (Non-Movers) by region

One explanation is that Austin and Silicon Valley have multiple institutional structures and entrepreneurial environments that promote social tie formation and embeddedness in these locations. In one of the interviews, Yaser Masoudnia, an entrepreneur who moved from Washingtion D.C. to Silicon Valley, spoke about the environment being an important factor in building a support network and growing their business.

> "We were based in DC area. And we realized very soon—I think it was about six or seven months into the business—that we are in the wrong place, despite the fact that a lot of part of the business that we were doing was basically security

> space and cyber security. We realized that if we want to make progress and make this business happening, we have to be in an environment with a network that nourished the start-ups and small businesses. That was the reason both of us moved from DC to basically Silicon Valley, and we start living here, working on the idea, going to different events, finding different people." (Yaser Masoudnia)

Descriptive indicators of the entrepreneurial ecosystems in Austin and Silicon Valley also lend support to this argument. Both Austin and Silicon Valley have a large number of incubators, accelerators, co-working spaces, social groups, and networking events targeting individuals with entrepreneurial ambitions. These formal organizations and informal groups frequently host networking events and activities on a weekly if not daily basis, thus increasing opportunities to interact (Startup Digest 2016). Frequency of interaction facilitates production and maintenance of close-knit networks (Blau 1964, Homans 1964). For example, Silicon Valley has dozens of well-known incubators including Y Combinator, Silicon Valley Innovation Center, 500 Startups, and Founders Space among many others.

In the interviews with entrepreneurs, many reported that meetups facilitated tie formation. Meetup[12] is a platform that enables local individuals to organize events around certain topics, ideas, activities, or groups. Although some entrepreneurs reported that they attend meetups for all types of activities and interests, many were characterizing their participation in meetups focused around startups and entrepreneurs. In another interviews, Joseph Dreyfus suggested that Meetups help entrepreneurs "find a community of people who have like interests and similar kind of expectations and ambitions."

The meetups can be geared towards entrepreneurs in general, but many are targeted towards specific subgroups based on interest or industry. For example, during field work for the analysis in this chapter, I attended meetups specifically targeting entrepreneurs interested in 3D printing, makers spaces, and crowdfunding on Kickstarter.

[12] https://www.meetup.com/

Another entrepreneur interviewee, Alec Olsson, suggested that it can be challenging building ties in the San Francisco Bay area (Silicon Valley) where seemingly everybody is an entrepreneur or has ambitions of launching a startup. In this context, Alec reported that these specialized meetups can helpful in connecting with individuals that are more relevant to your needs and interests.

> "San Francisco is crazy, because it seems like everyone and their brother in this city is involved in a start-up. And it's probably the one city I've been in in the world where when somebody asks you what you do for a living, if you say, "I work for a start-up," it's not of particular interest, and it's completely cliché. And so networking becomes challenging because there is no novelty associated with it. It's 100% expected to be associated with a start-up, and you have to find other ways and reasons to connect with people. So that can be industry specific. There are a bunch of industry specific meet-ups. There's the 3D printing meet-up. There's the advanced manufacturing meet-up. There's hardware start-up meet-ups, you know, where you can sort of form a cadre of like-minded, or at least like-focused companies or start-up founders." (Alec Olsson)

Incubators are other structures within startup ecosystems that can facilitate entrepreneur social capital formation. Some incubators aim to develop new products or technologies, but the typical aim of these organizations is to nurture and develop entrepreneurial talent and to encourage startups. Most incubators offer many services such as office space, business supplies/services, entrepreneurship courses, advisor/mentors, consultants, and access to labs and equipment (Allen and McCluskey 1991, Mian 1996). Some incubators offer small amounts of capital upon acceptance into the incubator. Also there are a few studies that suggest incubators help broker ties between entrepreneurs and key financial, technical, and social resources (Bøllingtoft and Ulhøi 2005, Totterman and Sten 2005). Some entrepreneurs I interviewed describe incubators as an alumni network of past members, who facilitated tie formation. Describing his experience in the Techstars incubator, Silicon Valley entrepreneur Devin Norris said:

> "It's been this kind of ever long fraternity, alumni, however you want to call it and we think very highly of the Techstars program. … We joined Techstars, which is now an international network of entrepreneurs and founders and mentors and while we completed that program in June of 2013 – or, sorry, we started it in June. I think we "graduated" in September or October for the – ever since we moved on, we still have – it's like an alumni network. It's like a modern day college in a sense and we still get a ton of value out of both helping other entrepreneurs and getting help ourselves." (Devin Norris)

Several entrepreneurs that had experience with incubators indicated that incubator personnel had established networks with first degree connections to key resources, particularly early seed capital investors. Alec Olsson reported:

> "First of all, from a fundraising perspective, you really—the only way you can effectively fundraise for venture capital is to have a good number of people in your network that know a good number of VCs and to get very strong personal introductions from the people in your network. And when we started the company in Madison, we literally knew nobody. So one of, you know, we paid—through our participation in Techstars—with a significant amount of equity in the company, and the thing we were buying with that equity was first and foremost access to the Techstars network … that would give us access to introductions to venture capitalists." (Alec Olsson)

In addition, Stanford University, an early champion of technology transfer and commercialization towards entrepreneurship, plays a big role in fostering the Silicon Valley startup ecosystem (Colyvas and Powell 2006). Similarly, in Austin, prominent incubators—including Capital factory, TechRanch, Techstars, Austin Technology Incubator, and Thinktiv—and The University of Texas at Austin also host many events in support of the Austin startup entrepreneurs. These events provide a forum for potential entrepreneurs to build network ties and access support structures and key resources for launching new ventures.

In general, the responses suggested that participation in incubators was valuable to very early stage entrepreneurs with small stocks of social capital, particularly entrepreneurs that recently arrived in a new location. For example, Joshua Serrano describes his experience arriving in Austin:

> "So when I first came here, I didn't know anybody and all I had was the Capital Factory [incubator] basically as a place to kind of start plugging into different places. But I was – you know, within six months to a year, I was connected to a lot of very useful, successful, and cool people in Austin. And it didn't – all it took was like me making them feel like I was really trying to do something positive for them to be like willing to help me and wanting to help me." (Joshua Serrano)

I find that "location stickiness", meaning the cumulative time spent in a location, significantly influences entrepreneurs when choosing a startup location. The results show that the more time entrepreneurs remain in a location increases the likelihood that they establish a startup in that same location. Interpreting the estimate for Austin entrepreneurs in Table 11 (model 1), I see that a one-year increase in cumulative time spent in Austin increases the odds of starting a company in Austin by 1.09 (statistically significant at 99% level). For entrepreneurs in Boston, Silicon Valley, and New York (Table 11, models 2, 3, and 4), I find a one-year increase in cumulative time spent in a location increased the odds of starting a company in that location by 1.15, 1.12, and 1.21, respectively (all estimates statistically significant at 99% level).

Regarding estimates for other individual-level factors, I find no statistically significant association between having a graduate degree and starting in company in the same location. In Boston and New York, I find a negative and significant association between overall cumulative work experience and entrepreneurs starting a company in the same location. For Boston and New York, a one-year increase in cumulative time in a location reduces the odds of starting a company in the same location by 0.069 and 0.104, respectively (estimates statistically significant at 99% level).

Reporting findings for the metropolitan-level factors, I find a positive and significant association between the number of funding opportunities for startups in Austin and Silicon Valley and entrepreneurs remaining in that location to start companies. For Austin and Silicon Valley (models 1 and 3 in Table 11), a 10 percent increase in the number of ln(funding rounds per year) increases the odds that entrepreneurs will stay in the same locations and start their companies by a factor of 1.07 and 1.05, respectively. The models also include a measure for the average funding amount per year, but the beta estimates were not statistically significant. This finding might stem from the type of industry prevalent each location. Austin and Silicon Valley produce a lot of information technology and software startups that have lower initial costs, thus large funding amounts may not be a primary concern at the initial stages. Moreover, although average funding amount and number of funding rounds are not strongly correlated (which is why they are simultaneously included in the model specifications), I tried removing funding rounds and leaving average funding rounds in the specification, but the results did not significantly change.

Moreover, this finding is consistent with the chapter's expectations based on numerous discussions with entrepreneurs and angel investors. In the interviews, entrepreneurs reported that they primarily seek small-to-medium sized investments from angel investors towards the beginning of the process and very few startups are equipped to appropriately utilize massive investment fusions that often come with steep growth targets that must be reached in a short period of time. Targeting large investment amounts is not a priority in the earliest phases of launching a company, although they might be relevant at a more mature phase. Thus during the startups' nascent phase, potential entrepreneurs are likely to be attracted to a location that provides more opportunities for funding when compared to the amount of funding. As a result, entrepreneurs believe that the larger number of funding rounds in a location is an indicator of more opportunity for securing funding for their startup. Additionally, because startups are typically funded in stages (Gompers and Lerner 2010), entrepreneurs likely associate more funding rounds in a location with a higher likelihood that their startup will continue to receive additional funding rounds beyond any initial investment capital. In short, for Austin and Silicon Valley, entrepreneurs tend to gravitate towards places where they have more opportunity for rounds of funding.

Regarding patents, I find three statistically significant associations. For Boston entrepreneurs, a 10 percent increase in the ln(number of patents per year) increases the odds ratio of entrepreneurs staying in the same locations and starting companies by a factor of 1.11, and this estimate is statistically significant ($p<0.01$). Again, industry type might offer an explanation. Boston has many startups in the biotechnology sector, which require large upfront investments for new entrants. Patents are important in the biotechnology sector for potential entrepreneurs and investors due to the large startup costs. This finding aligns with the importance of biotechnology to the Boston startup ecosystem. Conversely, I find a significant and negative association in Silicon Valley and New York. For Silicon Valley and New York entrepreneurs, a 10 percent increase in the ln(number of patents per year) reduces the odds of entrepreneurs staying in the same locations and starting companies by a factor of 0.04 and 0.11, respectively (both estimates statistically significant ($p<0.05$)%. The estimate is not statistically significant for entrepreneurs in Austin.

Next, I report estimates from Table 12 that present the estimated beta coefficients of logistic regressions for entrepreneurs who chose to change locations and start a company. In Table 12, the dependent variable is whether or not the entrepreneur moved to a different location and immediately started a company. The model specification is the same across all the models, except for the location stickiness variable. In Table 12, entrepreneurs change locations and the stickiness variable measures the cumulative work experience in the previous location (prior to the startup location). For the models in Table 12, this is the location of the previous job.

Logistic regression estimates for entrepreneurs who started companies in different location (move and immediately started company) by Region

	Dependent variable: Move and Immediately Founder			
	(1)	(2)	(3)	(4)
	Austin	Boston	S.V.	New York
Grad Degree	-0.115	-1.953	-0.286	-0.521
	(0.327)	(0.848)	(0.324)	(0.539)
Cumulative Work Experience (Yrs)	0.056***	0.150***	0.090***	0.161***
	(0.020)	(0.053)	(0.027)	(0.050)
Tie-Proportion in Previous Location	-2.272***	-3.388**	-4.624***	-0.739
	(0.701)	(1.586)	(0.864)	(1.088)
Cumulative Work Experience in Previous Location	-0.029	-0.173**	-0.043	-0.099*
	(0.030)	(0.082)	(0.031)	(0.060)
ln(Funding-Rounds Per Year)(1-yr lag)	0.344**	0.640**	1.096***	-0.164
	(0.166)	(0.343)	(0.237)	(0.197)
ln(Avg. Funding Per Year)(1-yr lag)	-0.035	-0.332**	1.655**	0.156
	(0.059)	(0.155)	(0.725)	(0.203)
ln(Number of Patents)(1-yr lag)	0.783***	1.459***	0.054	-0.856
	(0.208)	(0.545)	(0.228)	(0.546)
Constant	-8.995***	-11.489**	-35.773***	-0.302
	(1.770)	(4.652)	(12.576)	(4.671)
Economic Controls (metro-performance index)	yes	yes	yes	yes
Observations	709	178	922	414
Note: (Odds Ratios reported in text)	*p<0.1; **p<0.05; ***p<0.01			

Table 12: Logistic regression estimates for entrepreneurs who started companies in different location (move and immediately started company) by region

Logistic regression estimates for entrepreneurs who started companies in different location (move, work other job, then started company) by Region

	Dependent variable:			
	Move and Other-Job, Then Founder			
	(1)	(2)	(3)	(4)
	Austin	Boston	S.V.	New York
Grad Degree	0.010	20.263	0.031	-0.400
	(0.412)	(750.499)	(0.383)	(0.749)
Cumulative Work Experience (Yrs)	0.060**	-0.001	0.098***	0.200***
	(0.024)	(0.106)	(0.025)	(0.062)
Tie-Proportion (new location)	1.802**	-0.871	-0.942	-3.081
	(0.859)	(2.472)	(0.805)	(1.759)
Cumulative Work Experience in Previous Location	-0.155***	-0.066	-0.173***	-0.123*
	(0.052)	(0.144)	(0.049)	(0.074)
ln(Funding-Rounds Per Year)(1-yr lag)	0.826**	1.027	1.530***	1.177
	(0.335)	(1.028)	(0.467)	(0.827)
ln(Avg. Funding Per Year)(1-yr lag)	-0.168	2.190	-0.452	0.144
	(0.113)	(4.812)	(0.353)	(1.055)
ln(Number of Patents)(1-yr lag)	0.507	0.894	-0.527	-1.002
	(0.330)	(1.021)	(0.427)	(0.979)
Constant	-8.851***	-71.199	-3.277	-8.452
	(2.857)	(748.095)	(4.817)	(17.286)
Economic Controls (metro-performance index)	yes	yes	yes	yes
Observations	709	178	922	414
Note: (Odds Ratios reported in text)t	*p<0.1; **p<0.05; ***p<0.01			

Table 13: Logistic regression estimates for entrepreneurs who started companies in different location (move, work other job, then started company) by region

As shown in Table 12, the tie-proportion estimates are negative and significant for entrepreneurs changing locations and immediately starting companies in Austin, Boston, and Silicon Valley. If an entrepreneur's tie-proportion in their previous metropolitan area is high, the entrepreneur is less likely to immediately start a company after moving to a different location. This finding is consistent with expectations based on prior research. Social networks are important to launching startups because social capital allows the entrepreneurs to locate and mobilize important resources (e.g., initial seed funding, labor and human capital, strategic or technical expertise). Thus it is unlikely that entrepreneurs can launch new venture in a location where they have relatively few connections and support in the local community.

Looking at entrepreneurs starting companies in Boston and New York in Table 12, I see that a one-year increase in cumulative time in previous location reduces the odds of starting a company in Boston and New York by 0.16 and 0.09, respectively. The estimates for entrepreneurs in Austin and Silicon Valley were not statistically significant. I find having a graduate degree is not significantly associated with starting a company in a different location.

In all four locations I find a positive and significant association between cumulative work experience in a location and entrepreneurs starting a company after changing locations. For Austin, Boston, Silicon Valley, and New York, a one-year increase in cumulative time in a location increases the odds of starting a company immediately after changing locations by 1.06, 1.16, 1.09, and 1.17, respectively. This finding is consistent with the literature on commitment. The longer someone spends working in a career field, the more committed they become to a particular career ladder. Consequently, they are less likely to sacrifice their gains and lifestyle towards a highly risky venture as an entrepreneur. This could suggest why many entrepreneurs are young, often recent college graduates. However, the situation is different for individuals who change locations. Some individuals work quickly up the career ladder, often achieving high-status positions, yet remain professionally unfulfilled or experience a personal shock (e.g., divorce, death in family). Thus, they seek large changes like moving regions and seeking new experience, including risker career changes like starting their own company.

For Austin, Boston, and Silicon Valley (models 1 and 3 in Table 12), a 10 percent increase in the ln(number of funding rounds per year) increases the odds ratio of the entrepreneur changing locations and starting a company immediately by 1.03, 1.07, and 1.12, respectively ($p<.05$). Regarding patents, in Austin and Boston, I find a 10 percent increase in the ln(number of patents per year) increases the odds ratio of the entrepreneur changing locations and immediately starting a company in Austin and Boston by 1.08 and 1.16, respectively, and these estimate are statistically significant ($p<0.001$).

Lastly, I report estimates from Table 13 that present the estimated beta coefficients of logistic regressions for entrepreneurs who chose to change locations and start a company after working a short-term job. The dependent variable for Table 13 is whether or not the entrepreneur moved to a different location and started a company after a short delay (worked as an employee for a duration of one year or less before starting a company). To reiterate, the model specification is the same across all the models, except for the location stickiness variable. For the models in Table 13, this is the location of the job before the short-term job (because the short-term job is in the same location as the startup).

I find that tie-proportion is important for entrepreneurs moving to Austin to start a company after working short-term in another job. For persons moving from another region to Austin, I find the higher the person's tie-proportion in Austin the more likely the person will start a company in Austin after a short duration working as employee.

Interpreting model 1 in Table 13, for a 0.1 increase in the tie-proportion in a location, the odds of an entrepreneur starting a company in the new location after working for a short while increase by a factor of 1.20. This estimate is also statistically significant ($p<0.05$). However, this association was not significant for entrepreneurs moving to Silicon Valley, Boston, or New York.

One explanation for this finding is the ease or pace at which newcomers can get plugged into crucial networks within the startup ecosystem in Austin. This stems from many of the characteristics of Austin's ecosystem. For one, Austin's startup ecosystem is much smaller than the ecosystems in Silicon Valley and New York City. Based on the interview responses from entrepreneurs, the entrepreneurial ecosystem in Austin is often described as decentralized with more accessible channels to key players and influencers in the ecosystem. The culture of Austin's startup scene is also distinct, often described as friendly and collaborative, as I report from analysis of entrepreneur interviews. This is supported across multiple interviews with Austin entrepreneurs who have spent time in Silicon Valley, Boston, and other key cities. As one Austin entrepreneur moving from Silicon Valley puts it:

> "I think that in Austin, I mean – like compared to Silicon Valley, Austin startup culture has a very laid-back feel to it. Whereas I think you could look at the startup culture in Silicon Valley as very well defined, very, you know, 'This is what a startup is supposed to look like'—everyone trying to be more disruptive to the industry. I don't know how you translate that necessarily. I just think [Austin] has a little bit more collaborative culture. For example, we try very hard to collaborate with other industry providers in Austin." (Jeff Smith)

I find the estimates for location stickiness were negative and significant for all locations among entrepreneurs who move to a new location, work as an employee for a short while and then start a company. For Austin, Silicon Valley, and New York, a one-year increase in cumulative time in a location reduces the odds of moving to another location by 0.14, 0.16, and 0.12, respectively. These estimates align with expectations from prior research suggesting some degree of geographic inertia or local stickiness. Entrepreneurs' tend to become more attached to a location as their tenure in that location increases and therefore are less likely to move elsewhere to start a company (Dahl and Sorenson 2012).

I find that having a graduate degree is not significantly associated with starting a company in a different location. For Austin, Silicon Valley, and New York, a one-year increase in cumulative work experience increases the odds of this occurring by 1.06, 1.10, and 1.22, respectively ($p<.05$).

For Austin and Silicon Valley (models 1 and 3 in Table 13), a 10 percent increase in the number of funding rounds per year increases the odds ratio of the entrepreneur working a short-term job, and then starting a company by a factor of 1.09 and 1.17, respectively. All these estimates are statistically significant ($p<0.001$). For Boston and New York, the estimates were positive but not statistically significant.

As explained above, I find a positive and significant influence of an entrepreneur's tie-proportion on their likelihood to start a company in a location. However, one might suggest that evolution of tie-proportion in a location be correlated with an individual's tenure in that location. While I do not have time series data on the evolution of social networks, I address this concern by testing the results by simulating the tie-proportion in a metropolitan area based on entrepreneurs' tenures in current and past locations. The dynamic tie-proportion in this chapter is created the same way as described in chapter 2 (above).

A well-documented finding in the literature is that relationships are more likely to develop between co-located persons. In many social contexts, the likelihood of any tie formation decreases rapidly as the physical distance separating two parties increases

(Bossard 1932, Kono et al. 1998b, Sorenson and Stuart 2001). At the dyadic level, co-location increases the likelihood of interaction between two parties and there is a tendency toward mutuality in relations over time because of the social pressure to reciprocate interactions (Gouldner 1960). Because tie-proportion is simply the connections in a location divided by the total connections in all locations, a dynamic conception of entrepreneurs' tie-proportion is a function of the tenure in current and past locations. Formally, this new dynamic measure of tie-proportion is:

$$td_{ij\tau} = \frac{n_{ij} * \left(\sum_{t\in[0,\tau]} t_{ij}\right)/\left(\sum_{t\in[0,T]} t_{ij}\right)}{\sum_j \left(n_{ij} * \left(\sum_{t\in[0,\tau]} t_{ij}\right)/\left(\sum_{t\in[0,T]} t_{ij}\right)\right)}$$

Here, td is the time varying tie-proportion of an individual, t is a dummy representing a unit of time spent in location j by individual i, n the observed number of ties of individual i in location j, and τ represents the time period in consideration. Thus, I converted the static view of tie-proportion per location into a time varying dynamic tie-proportion panel. I find that that such panel of tie-proportion does not affect the results in any significant way, thus reinforcing the findings reported above.

CONCLUSION

Technology regions are continually being transformed by entrepreneurship. This study investigated four prominent entrepreneurial ecosystems in the U.S. that have been explored in the massive literature on regional advantage. I examined location-specific variation in the influence of social networks, funding opportunities, and economic factors on entrepreneur location choices. I provided measures for operationalizing the technopolis wheel, a conceptual model designed to show institutional structures which are important for technology regions to develop and continue to re-invent themselves. Moreover, the supplementary analysis of interviews from entrepreneurs from Austin and

Silicon Valley highlighted structural and cultural aspects of particular entrepreneurial ecosystems. These responses offered potential explanations for some of the location-specific variation in the influence of social networks, funding opportunities, and economic factors on entrepreneur location choice.

This study shows the importance of studying education, cumulative work experience and the proportion of ties when investigating why entrepreneurs stay or move to particular locations to launch technology startups. One empirical finding is that social networks in Austin and Silicon Valley are an important factor in retaining potential entrepreneurs. Additional support for this finding was reported in the interviews with entrepreneurs in Austin and Silicon Valley. Entrepreneur responses support the explanation that these locations have strong institutional structures that promote the creation of social ties and thus increasing one's embeddedness in these locations. Entrepreneurs consistently reported on particular structures within entrepreneurial ecosystems that were central to them building their social network including social groups/clubs, Meetsups, startup/entrepreneur-centric events, and incubators. It was clear from several interviews that social groups and meetups played an important role in entrepreneur tie formation. Institutional structures are important in fostering network ties, which impact entrepreneurs' ability to access and mobilize the resources necessary to launch new ventures.

Furthermore, the ease or pace at which newcomers can get plugged into crucial networks could be an important factor in creating or sustaining a healthy startup ecosystem. For persons moving from another region to Austin, I find the higher the person's tie-proportion in Austin the more likely the person will start a company in Austin after a short duration working as an employee. Based on the interviews, it is plausible that this finding stems from many of the characteristics of Austin's distinct ecosystem. For one, Austin's startup ecosystem is much smaller than the Silicon Valley and New York. Several interview responses characterize the entrepreneurial ecosystem in Austin as more decentralized with more accessible channels to key players and influencers in the Austin ecosystem. Based on the interviews, this environment could be derived from Austin's distinct culture, which was often described as more friendly and collaborative relative to the ecosystems in Silicon Valley, Boston, and New York. This is supported across multiple interviews with Austin entrepreneurs who have spent time in Silicon Valley, Boston, and other key cities.

I also found that the number of funding rounds per year, or frequency of opportunities for funding in a location, seems to influence whether or not an entrepreneurs move elsewhere to start a venture. I should note that it is the number of rounds rather than the average funding amount per year that appears to influence entrepreneur location choices. More research is needed to help validate this finding in the analysis. Once corroborated with additional research studies, this finding could be very important to state and city policy makers. City officials might consider policies that encourage the organization of angel networks, which fund more seed investment rounds relative to the large capital infusions by venture capital firms (e.g. series A, series B, series C). These policies might include financial and other regulatory incentives. This seems particularly relevant to declining industrial metropolitan areas with stagnating local economies, which are striving to encourage local entrepreneurship and retain local talent that is flowing to cities like the San Francisco Bay Area, Austin, Boston, and New York City. Access to sufficient investment is widely perceived, in the entrepreneurial community, to be the dominant impediment to startup success. Thus, future studies should further test this association, perhaps exploring potential moderating factors that could establish indirect relationships.

References

Abbott, Andrew and Alexandra Hrycak. 1990. "Measuring Resemblance in Sequence Data: An Optimal Matching Analysis of Musicians' Careers." *American Journal of Sociology* 96(1):144-85. doi: 10.1086/229495.

Abbott, Andrew and Angela Tsay. 2000. "Sequence Analysis and Optimal Matching Methods in Sociology: Review and Prospect." *Sociological Methods & Research* 29(1):3-33. doi: Doi 10.1177/0049124100029001001.

Ács, Zoltán J. and David B. Audretsch. 2003. *Handbook of Entrepreneurship Research: An Interdisciplinary Survey and Introduction*, Vol. 1.;1;. Boston: Kluwer.

Agarwal, Rajshree, Raj Echambadi, April M. Franco and Mb Sarkar. 2004. "Knowledge Transfer through Inheritance: Spin-out Generation, Development, and Survival." *The Academy of Management Journal* 47(4):501-22.

Aggarwal, R. and H. Singh. 2013. "Differential Influence of Blogs across Different Stages of Decision Making: The Case of Venture Capitalists." *MIS Quarterly* 37(4):1093-93.

Aggarwal, Rohit, Ram Gopal, Alok Gupta and Harpreet Singh. 2012a. "Putting Money Where the Mouths Are: The Relation between Venture Financing and Electronic Word-of-Mouth." *Information Systems Research* 23(3-part-2):976-92. doi: 10.1287/isre.1110.0402.

Aggarwal, Rohit, Ram Gopal, Ramesh Sankaranarayanan and Param Vir Singh. 2012b. "Blog, Blogger, and the Firm: Can Negative Employee Posts Lead to Positive Outcomes?". *Information Systems Research* 23(2):306-22. doi: 10.1287/isre.1110.0360.

Aggarwal, Rohit, David Kryscynski and Harpreet Singh. 2015. "Evaluating Venture Technical Competence in Venture Capitalist Investment Decisions." *Management Science* 61(11):2685-706. doi: 10.1287/mnsc.2014.2117.

Alcacer, J. and W. Chung. 2007. "Location Strategies and Knowledge Spillovers." *Management Science* 53(5):760-76. doi: 10.1287/mnsc.1060.0637.

Allen, David N. and Richard McCluskey. 1991. "Structure, Policy, Services, and Performance in the Business Incubator Industry." *Entrepreneurship Theory and Practice* 15(2):61-77.

Amit, Raphael, Lawrence Glosten and Eitan Muller. 1990. "Entrepreneurial Ability, Venture Investments, and Risk Sharing." *Management Science* 36(10):1233-46. doi: 10.1287/mnsc.36.10.1233.

Amit, Raphael, Eitan Muller and Iain Cockburn. 1995. "Opportunity Costs and Entrepreneurial Activity." *Journal of Business Venturing* 10(2):95-106.

Aral, Sinan and Dylan Walker. 2012. "Identifying Influential and Susceptible Members of Social Networks." *Science* 337(6092):337-41.

Åstebro, Thomas and Peter Thompson. 2011. "Entrepreneurs, Jacks of All Trades or Hobos?". *Research Policy* 40(5):637-49. doi: 10.1016/j.respol.2011.01.010.

Azoulay, Pierre, Benjamin Jones, Daniel Kim and Javier Miranda. 2017. "Age and High-Growth Entrepreneurship." *NBER Entrepreneurship Workshop*.

Baker, Wayne E. 1984. "The Social Structure of a National Securities Market." *American Journal of Sociology*:775-811.

Baroudi, Jack J. and Magid Igbaria. 1994. "An Examination of Gender Effects on Career Success of Information Systems Employees." *Journal of Management Information Systems* 11(3):181-201.

Baum, J. A. C., T. Calabrese and B. S. Silverman. 2000. "Don't Go It Alone: Alliance Network Composition and Startups' Performance in Canadian Biotechnology." *Strategic Management Journal* 21(3):267-94. doi: Doi 10.1002/(Sici)1097-0266(200003)21:3<267::Aid-Smj89>3.0.Co;2-8.

Bearman, Peter. 1997. "Generalized Exchange 1." *American Journal of Sociology* 102(5):1383-415.

Becker, Howard Saul. 1952. "The Career of the Chicago Public Schoolteacher." *American Journal of Sociology* 57(5):470-77. doi: Doi 10.1086/221015.

Bennett, Victor Manuel, Megan Lawrence and Raffaella Sadun. 2016. "Are Founder Ceos Good Managers?" in *Measuring Entrepreneurial Businesses: Current Knowledge and Challenges*: University of Chicago Press.

Bertaux, Daniel. 1982. *The Life Course Approach as a Challenge to the Social Sciences*, Edited by T. K. Hareven and K. J. Adams. New York: Guilford.

Bertrand, Marianne and Antoinette Schoar. 2003. "Managing with Style: The Effect of Managers on Firm Policies." *The Quarterly Journal of Economics* 118(4):1169-208.

Bharadwaj, A., O. A. El Sawy, P. A. Pavlou and N. Venkatraman. 2013. "Digital Business Strategy: Toward a Next Generation of Insights." *MIS quarterly* 37(2):471-82.

Bidwell, Matthew and Forrest Briscoe. 2010. "The Dynamics of Interorganizational Careers." *Organization Science* 21(5):1034-53. doi: 10.1287/orsc.1090.0492.

Bidwell, Matthew and Ethan Mollick. 2015. "Shifts and Ladders: Comparing the Role of Internal and External Mobility in Managerial Careers." *Organization Science* 26(6):1629-45. doi: 10.1287/orsc.2015.1003.

Blau, Peter Michael. 1964. *Exchange and Power in Social Life*. New York: J. Wiley.

Blau, Peter Michael and Otis Dudley Duncan. 1967. *The American Occupational Structure*. New York: Wiley.

Bloom, Nicholas and John Van Reenen. 2007. "Measuring and Explaining Management Practices across Firms and Countries." *The Quarterly Journal of Economics* 122(4):1351-408.

Bøllingtoft, Anne and John P. Ulhøi. 2005. "The Networked Business Incubator—Leveraging Entrepreneurial Agency?". *Journal of Business Venturing* 20(2):265-90. doi: 10.1016/j.jbusvent.2003.12.005.

Boskin, Michael J. 1974. "A Conditional Logit Model of Occupational Choice." *The Journal of Political Economy*:389-98.

Bossard, James H. S. 1932. "Residential Propinquity as a Factor in Marriage Selection." *American Journal of Sociology*:219-24.

Bourdieu, Pierre. 1986. "The Forms of Capital." Pp. 241-58, Vol. 241.

Brynjolfsson, Erik and Andrew McAfee. 2011. "Race against the Machine: How the Digital Revolution Is Accelerating Innovation, Driving Productivity, and Irreversibly Transforming Employment and the Economy." *Amazon Digital Services*.

Buenstorf, Guido and Steven Klepper. 2009. "Heritage and Agglomeration: The Akron Tyre Cluster Revisited*." *The Economic Journal* 119(537):705-33.

Burt, Ronald S. 2004. "Structural Holes and Good Ideas." *American Journal of Sociology* 110(2):349-99. doi: 10.1086/421787.

Butler, John and David Gibson. 2011. *Global Perspectives on Technology Transfer and Commercialization*: Edward Elgar Publishing.

Butler, John S. 2010. "The University of Texas at Austin." in *The Development of University-Based Entrepreneurship Ecosystems*, edited by M. Fetters, P. Greene, M. Rice and J. Butler: Edward Elgar Publishing.

Bygrave, William, Michael Hay, Emily Ng and Paul Reynolds. 2003. "Executive Forum: A Study of Informal Investing in 29 Nations Composing the Global Entrepreneurship Monitor." *Venture Capital: An International Journal of Entrepreneurial Finance* 5(2):101-16.

Campbell, Benjamin A., Martin Ganco, April M. Franco and Rajshree Agarwal. 2012. "Who Leaves, Where to, and Why Worry? Employee Mobility, Entrepreneurship and Effects on Source Firm Performance." *Strategic Management Journal* 33(1):65-87.

Cappelli, Peter and Monika Hamori. 2014. "Understanding Executive Job Search." *Organization Science* 25(5):1511-29. doi: 10.1287/orsc.2013.0871.

Castilla, Emilio J., Hokyu Hwang, Ellen Granovetter and Mark Granovetter. 2000. "Social Networks in Silicon Valley." *The Silicon Valley edge: A habitat for innovation and entrepreneurship*:218-47.

Chan, T. W. 1995. "Optimal Matching Analysis: A Methodological Note on Studying Career Mobility." *Work and Occupations* 22(4):467-90. doi: Doi 10.1177/0730888495022004005.

Coleman, James S. 1988. "Social Capital in the Creation of Human Capital." Pp. S95-S95, Vol. 94.

Colyvas, Jeannette a and Walter W. Powell. 2006. "Roads to Institutionalization: The Remaking of Boundaries between Public and Private Science." *Research in Organizational Behavior* 27(06):305-53. doi: 10.1016/S0191-3085(06)27008-4.

Conti, Annamaria, Marie Thursby and Frank T. Rothaermel. 2010. "Show Me What You Have: Signaling, Angel and Vc Investments in Technology Startups." *Academy of Management Annual Meeting Proceedings* 8(1):1-6. doi: 10.5465/AMBPP.2010.54493650.

Cooper, Arnold C. and William C. Dunkelberg. 1986. "Entrepreneurship and Paths to Business Ownership." *Strategic Management Journal* 7(1):53-68.

Cooper, Arnold C., Carolyn Y. Woo and William C. Dunkelberg. 1989. "Entrepreneurship and the Initial Size of Firms." *Journal of Business Venturing* 4(5):317-32. doi: 10.1016/0883-9026(89)90004-9.

Cooper, S. Y. and J. S. Park. 2008. "The Impact of `Incubator' Organizations on Opportunity Recognition and Technology Innovation in New, Entrepreneurial High-Technology Ventures." *International Small Business Journal* 26(1):27-56. doi: 10.1177/0266242607084658.

Dahl, Michael and Olav Sorenson. 2009. "The Embedded Entrepreneur." *European management review* 6(3):172-81.

Dahl, Michael and Olav Sorenson. 2010. "The Social Attachment to Place." *Social Forces* 89(2):633-58.

Dahl, Michael and Olav Sorenson. 2012. "Home Sweet Home: Entrepreneurs' Location Choices and the Performance of Their Ventures." *Management Science* 58(6):1059-71. doi: 10.1287/mnsc.1110.1476.

Davidsson, Per and Benson Honig. 2003. "The Role of Social and Human Capital among Nascent Entrepreneurs." *Journal of Business Venturing* 18(3):301-31. doi: 10.1016/s0883-9026(02)00097-6.

De Meo, Pasquale, Emilio Ferrara, Giacomo Fiumara and Alessandro Provetti. 2014. "On Facebook, Most Ties Are Weak." Pp. 78-84, Vol. 57. NEW YORK: ACM.

DeFillippi, Robert J. and Michael B. Arthur. 1996. "Boundaryless Contexts and Careers: A Competency-Based Perspective." *The boundaryless career: A new employment principle for a new organizational era*:116-31.

Deming, David. 2017. "The Growing Importance of Social Skills in the Labor Market." *National Bureau of Economic Research*.

Digest, Startup. 2016. (https://www.startupdigest.com/).

DiNapoli, Thomas and Kenneth Bleiwas. 2014. "New York City's Growing High-Tech Industry." *Office of the State Comptroller Report*.

Dlouhy, Katja and Torsten Biemann. 2015. "Optimal Matching Analysis in Career Research: A Review and Some Best-Practice Recommendations." *Journal of Vocational Behavior* 90:163-73. doi: 10.1016/j.jvb.2015.04.005.

Dorfman, Nancy S. 1983. "Route 128: The Development of a Regional High Technology Economy." *Research Policy* 12(6):299-316. doi: http://dx.doi.org/10.1016/0048-7333(83)90009-4.

Engel, Jerome S. 2015. "Global Clusters of Innovation: Lessons from Silicon Valley." *California management review* 57(2):36-65.

Engstrom, Therese. 1987. "Little Silicon Valleys." *High Technology* 7(January):24-33.

Etzkowitz, Henry and Loet Leydesdorff. 1997. "Universities in the Global Economy: A Triple Helix of University-Industry-Government Relations." *Cassell Academic, London*.

Etzkowitz, Henry and Loet Leydesdorff. 2000. "The Dynamics of Innovation: From National Systems and "Mode 2" to a Triple Helix of University–Industry–Government Relations." *Research Policy* 29(2):109-23.

Etzkowitz, Henry and James Dzisah. 2008. "Unity and Diversity in High-Tech Growth and Renewal: Learning from Boston and Silicon Valley." *European Planning Studies* 16(8):1009-24. doi: 10.1080/09654310802315385.

Evans, David S. and Linda S. Leighton. 1989. "Some Empirical Aspects of Entrepreneurship." *The American Economic Review* 79(3):519.

Evans, Mariah D. and Edward O. Laumann. 1983. "Professional Commitment: Myth or Reality." *Research in Social Stratification and Mobility* 2:3-40.

Ewens, Michael and Matt Marx. 2017. "Founder Replacement and Startup Performance." *The Review of Financial Studies*.

Fallick, Bruce, Charles A. Fleischman and James B. Rebitzer. 2006. "Job-Hopping in Silicon Valley: Some Evidence Concerning the Microfoundations of a High-Technology Cluster." *The Review of Economics and Statistics* 88(3):472-81. doi: 10.1162/rest.88.3.472.

Feldman, Daniel C. 2001. "Career Coaching: What Hr Professionals and Managers Need to Know." *Human Resource Planning* 24(2):26-35.

Feldman, Maryann P. 2000. "Location and Innovation: The New Economic Geography of Innovation, Spillovers, and Agglomeration." *The Oxford handbook of economic geography*:373-94.

Ferrary, Michel and Mark Granovetter. 2009. "The Role of Venture Capital Firms in Silicon Valley's Complex Innovation Network." *Economy and Society* 38(2):326-59. doi: 10.1080/03085140902786827.

Fetters, Michael, Patricia Greene, Mark Rice and John S. Butler. 2010. *The Development of University-Based Entrepreneurship Ecosystems*: Edward Elgar Publishing.

Figueiredo, O., P. Guimaraes and D. Woodward. 2002. "Home-Field Advantage: Location Decisions of Portuguese Entrepreneurs." *Journal of Urban Economics* 52(2):341-61. doi: Pii S0094-1190(02)00006-2.

Florida, Richard L. 2005. *Cities and the Creative Class*. New York: Routledge.

Foss, Lene and David V. Gibson. 2015. *The Entrepreneurial University: Context and Institutional Change*, Vol. 37.;37;. New York: Routledge.

Galasso, Alberto and Timothy S. Simcoe. 2011. "Ceo Overconfidence and Innovation." *Management Science* 57(8):1469-84.

Ganco, Martin. 2013. "Cutting the Gordian Knot: The Effect of Knowledge Complexity on Employee Mobility and Entrepreneurship." *Strategic Management Journal* 34(6):666-86. doi: 10.1002/smj.2044.

Ganco, Martin, Rosemarie H. Ziedonis and Rajshree Agarwal. 2015. "More Stars Stay, but the Brightest Ones Still Leave: Job Hopping in the Shadow of Patent Enforcement." *Strategic Management Journal* 36(5):659-85. doi: 10.1002/smj.2239.

Garg, Rajiv, Michael D. Smith and Rahul Telang. 2011. "Measuring Information Diffusion in an Online Community." *Journal of Management Information Systems* 28(2):11-38.

Garg, Rajiv and Rahul Telang. 2011. "To Be or Not to Be Linked on Linkedin: Job Search Using Online Social Networks." *Available at SSRN:* http://ssrn.com/abstract=1813532 *or* http://dx.doi.org/10.2139/ssrn.1813532.

Gibson, David V. and John S. Butler. 2013. "Sustaining the Technopolis: The Case of Austin, Texas." *World Technopolis Review* 2(2):64-80. doi: 10.7165/wtr2013.2.2.64.

Glaeser, Edward L., Stuart S. Rosenthal and William C. Strange. 2010. "Urban Economics and Entrepreneurship." *Journal of Urban Economics* 67(1):1-14. doi: 10.1016/j.jue.2009.10.005.

Gompers, Paul and Josh Lerner. 2010. "Equity Financing." Pp. 183-214 in *Handbook of Entrepreneurship Research*: Springer.

Gouldner, Alvin W. 1960. "The Norm of Reciprocity: A Preliminary Statement." *American sociological review*:161-78.

Greenhaus, Jeffrey H., Gerard A. Callanan and Marco DiRenzo. 2008. "A Boundaryless Perspective on Careers." *Handbook of organizational behavior*:277-99.

Greenwood, Brad N. and Anand Gopal. 2015. "Research Note—Tigerblood: Newspapers, Blogs, and the Founding of Information Technology Firms." *Information Systems Research* 26(4):812-28. doi: 10.1287/isre.2015.0603.

Greenwood, Brad N. and Anandasivam Gopal. Forthcoming. "Ending the Mending Wall: Herding, Media Coverage, and Colocation in It Entrepreneurship." *MIS quarterly*.

Hall, Oswald. 1948. "The Stages of a Medical Career." *American Journal of Sociology* 53(5):327-36.

Hallen, B. L. and K. M. Eisenhardt. 2012. "Catalyzing Strategies and Efficient Tie Formation: How Entrepreneurial Firms Obtain Investment Ties." *Academy of Management Journal* 55(1):35-70. doi: 10.5465/amj.2009.0620.

Heger, Diana, Tobias Veith and Miriam Rinawi. 2011. "The Effect of Broadband Infrastructure on Entrepreneurial Activities: The Case of Germany." *SSRN Electronic Journal*.

Hellmann, Thomas. 2000. "Venture Capitalists: The Coaches of Silicon Valley." Pp. 276-94: Stanford, CA: Stanford University Press.

Hellmann, Thomas and Manju Puri. 2002. "Venture Capital and the Professionalization of Start-up Firms: Empirical Evidence." *The journal of finance* 57(1):169-97.

Henton, Doug and Kim Held. 2013. "The Dynamics of Silicon Valley: Creative Destruction and the Evolution of the Innovation Habitat." *Social Science Information* 52(4):539-57.

Hermalin, Benjamin E. 1994. "Heterogeneity in Organizational Form: Why Otherwise Identical Firms Choose Different Incentives for Their Managers." *The RAND Journal of Economics*:518-37.

Hite, Julie M. and William S. Hesterly. 2001. "The Evolution of Firm Networks: From Emergence to Early Growth of the Firm." *Strategic Management Journal* 22(3):275-86. doi: 10.1002/smj.156.

Hite, Julie M. 2005. "Evolutionary Processes and Paths of Relationally Embedded Network Ties in Emerging Entrepreneurial Firms." *Entrepreneurship Theory and Practice* 29(1):113-44. doi: 10.1111/j.1540-6520.2005.00072.x.

Homans, G. C. 1964. "Bringing Men Back In." *American sociological review* 29(6):809-18.

Hsu, David H. 2006. "Venture Capitalists and Cooperative Start-up Commercialization Strategy." *Management Science* 52(2):204-19. doi: 10.2307/20110499.

Joseph, D., K. Y. Ng, C. Koh and S. Ang. 2007. "Turnover of Information Technology Professionals: A Narrative Review, Meta-Analytic Structural Equation Modeling, and Model Development." *MIS quarterly* 31(3):547-77.

Joseph, D., W. F. Boh, S. Ang and S. A. Slaughter. 2012. "The Career Paths Less (or More) Traveled: A Sequence Analysis of It Career Histories, Mobility Patterns, and Career Success." *MIS quarterly* 36(2):427-52.

Kahn, Robert L., D. Wolfe, R. Quinn, J. Snoek and R. Rosenthal. 1964. *Organizational Stress: Studies in Role Conflict and Ambiguity*. New York: Wiley.

Kalleberg, Arne L. and Paula M. Hudis. 1979. "Wage Change in the Late Career: A Model for the Outcomes of Job Sequences." *SOCIAL SCIENCE RESEARCH* 8(1):16-40. doi: 10.1016/0049-089X(79)90012-7.

Katona, George and James N. Morgan. 1952. "The Quantitative Study of Factors Determining Business Decisions." *The Quarterly Journal of Economics*:67-90.

Keller, J. R. 2017. "Posting and Slotting: How Hiring Processes Shape the Quality of Hire and Compensation in Internal Labor Markets." *Administrative Science Quarterly*. doi: 10.1177/0001839217736045.

Kennedy, R. Bryan and D. Ashley Kennedy. 2004. "Using the Myers-Briggs Type Indicator® in Career Counseling." *Journal of employment counseling* 41(1):38-43.

Kenney, Martin and Urs Von Burg. 1999. "Technology, Entrepreneurship and Path Dependence: Industrial Clustering in Silicon Valley and Route 128." *Industrial and Corporate Change* 8(1):67-103.

Kibler, E. 2013. "Formation of Entrepreneurial Intentions in a Regional Context." *Entrepreneurship and Regional Development* 25(3-4):293-323. doi: Doi 10.1080/08985626.2012.721008.

Kickul, Jill R. and Bala Mulloth. 2015. "New York University: Nurturing Entrepreneurship in New York City." Pp. 18-34 in *The Entrepreneurial University*: Routledge.

Kim, Keongtae, Sunil Mithas, Jonathan Whitaker and Prasanto K. Roy. 2014. "Research Note—Industry-Specific Human Capital and Wages: Evidence from the Business

Process Outsourcing Industry." *Information Systems Research* 25(3):618-38. doi: 10.1287/isre.2014.0532.

Klepper, Steven. 2010. "The Origin and Growth of Industry Clusters: The Making of Silicon Valley and Detroit." *Journal of Urban Economics* 67(1):15-32. doi: 10.1016/j.jue.2009.09.004.

Koch, Michael, Bernard Forgues and Vanessa Monties. 2017. "The Way to the Top: Career Patterns of Fortune 100 Ceos." *Human Resource Management* 56(2):267-85. doi: 10.1002/hrm.21759.

Kono, Clifford, Donald Palmer, Roger Friedland and Matthew Zafonte. 1998a. "Lost in Space: The Geography of Corporate Interlocking Directorates." *American Journal of Sociology* 103(4):863-911. doi: 10.1086/231292.

Kono, Clifford, Donald Palmer, Roger Friedland and Matthew Zafonte. 1998b. "Lost in Space: The Geography of Corporate Interlocking Directorates 1." *American Journal of Sociology* 103(4):863-911.

Kotkin, Joel and Mark Schill. 2015, "The Valley and the Upstarts: The Cities Creating the Most Tech Jobs", Innovation Daily- New Geography. (http://innovationamerica.us/index.php/innovation-daily/45694-the-valley-and-the-upstarts-the-cities-creating-the-most-tech-jobs-newgeographycom?utm_source=innovation-daily---your-daily-newsletter-highlighting-global-innovation-news-and-trends&utm_medium=gazetty&utm_campaign=04-16-2015).

Kozmetsky, G., M. Gill and R. W. Smilor. 1985. *Financing and Managing Fast- Growth Companies: The Venture Capital Process*. Lexington, MA: Lexington Books.

Krabel, Stefan and Pamela Mueller. 2009. "What Drives Scientists to Start Their Own Company?: An Empirical Investigation of Max Planck Society Scientists." *Research Policy* 38(6):947-56. doi: http://dx.doi.org/10.1016/j.respol.2009.02.005.

Krugman, Paul R. and Maurice Obstfeld. 1997. *International Economics : Theory and Policy*. Reading, Mass.: Addison-Wesley.

Lazear, Edward. 2004. "Balanced Skills and Entrepreneurship." *The American Economic Review* 94(2):208-11. doi: Doi 10.1257/0002828041301425.

Lee, Kibeom, Julie J. Carswell and Natalie J. Allen. 2000. "A Meta-Analytic Review of Occupational Commitment: Relations with Person- and Work-Related Variables." *Journal of Applied Psychology* 85(5):799-811. doi: 10.1037/0021-9010.85.5.799.

Leung, Ming D. 2014. "Dilettante or Renaissance Person? How the Order of Job Experiences Affects Hiring in an External Labor Market." *American sociological review* 79(1):136-58. doi: 10.1177/0003122413518638.

Lin, Nan. 2001. *Social Capital: A Theory of Social Structure and Action*: Cambridge: Cambridge University Press.

Lyness, Karen S. and Donna E. Thompson. 2000. "Climbing the Corporate Ladder: Do Female and Male Executives Follow the Same Route?". *Journal of Applied Psychology* 85(1):86-101. doi: 10.1037/0021-9010.85.1.86.

MacCrory, Frank, Vidyanand Choudhary and Alain Pinsonneault. 2016. "Research Note—Designing Promotion Ladders to Mitigate Turnover of It Professionals." *Information Systems Research* 27(3):648-60. doi: 10.1287/isre.2016.0652.

Marshall, Alfred. 1920. *Principles of Economics: An Introductory Volume*. London U6: Macmillan.

Massey, Douglas S. 1990. "Social Structure, Household Strategies, and the Cumulative Causation of Migration." *Population index*:3-26.

Maurer, Indre and Mark Ebers. 2006. "Dynamics of Social Capital and Their Performance Implications: Lessons from Biotechnology Start-Ups." *Administrative Science Quarterly* 51(2):262-92. doi: 10.2189/asqu.51.2.262.

McLaughlin, Heather. 2015: Business Wire. (https://www.businesswire.com/news/home/20150728005242/en/Three-Fourths-U.S.-Workers-30s-Career-Change-Reveals).

Mian, Sarfraz A. 1996. "Assessing Value-Added Contributions of University Technology Business Incubators to Tenant Firms." *Research Policy* 25(3):325-35.

Michaelides, Marios. 2011. "The Effect of Local Ties, Wages, and Housing Costs on Migration Decisions." *The Journal of Socio-Economics* 40(2):132-40. doi: 10.1016/j.socec.2011.01.010.

Michelacci, Claudio and Olmo Silva. 2007. "Why So Many Local Entrepreneurs?". *The Review of Economics and Statistics* 89(4):615-33.

Mimno, David and Andrew McCallum. 2008. "Modeling Career Path Trajectories."

Monkeylearn. 2016. "API Business Classifier." (https://app.monkeylearn.com/main/classifiers/cl_4PFzSWVR/)

Moore, James F. 1993. "Predators and Prey: A New Ecology of Competition." *Harvard business review* 71(3):75-83.

Moore, James F. 1996. *The Death of Competition: Leadership and Strategy in the Age of Business Ecosystems*, Vol. 1st. New York: HarperBusiness.

Morelix, Arnobio, Robert Fairlie, Joshua Russell and E.J. Reedy. 2015, "The Kauffman Index: Startup Activity-Metropolitan Area and City Trends". (http://www.kauffman.org/~/media/kauffman org/research reports and covers/2015/05/kauffman index startup activity metro trends 2015.pdf).

Mueller, Eva and James N. Morgan. 1962. "Location Decisions of Manufacturers." *The American Economic Review*:204-17.

Network, Central Texas Angel. 2016. (http://centraltexasangelnetwork.com/).

Owen Smith, Jason and Walter W. Powell. 2005. "Accounting for Emergence and Novelty in Boston and Bay Area Biotechnology." in *Cluster Genesis: The Emergence of Technology Clusters and the Implication for Government Policies*, edited by P. Braunerhjelm and M. Feldman.

Owen-Smith, Jason and Walter W. Powell. 2004. "Knowledge Networks as Channels and Conduits: The Effects of Spillovers in the Boston Biotechnology Community." *Organization Science* 15(1):5-21. doi: 10.1287/orsc.1030.0054.

Parwada, Jerry T. 2008. "The Genesis of Home Bias? The Location and Portfolio Choices of Investment Company Start-Ups." *Journal of Financial and Quantitative Analysis* 43(01):245-66.

Peters, Basil. 2009. *Early Exits: Exit Strategies for Entrepreneurs and Angel Investors (but Maybe Not Venture Capitalists)*: Basil Peters.

Petriglieri, Gianpiero, Jennifer Louise Petriglieri and Jack Denfeld Wood. 2017. "Fast Tracks and Inner Journeys: Crafting Portable Selves for Contemporary Careers." *Administrative Science Quarterly*. doi: 10.1177/0001839217720930.

PitchBook. 2016. (http://pitchbook.com/).

Porter, Michael E. 1990. *The Competitive Advantage of Nations*. New York: Free Press.

Porter, Michael E. 1998. "Cluster and the New Economics of Competition."

Powell, Walter W. 1996. "Inter-Organizational Collaboration in the Biotechnology Industry." *Journal of Institutional and Theoretical Economics (JITE)/Zeitschrift für die gesamte Staatswissenschaft*:197-215.

Powell, Walter W., Kenneth W. Koput, James I. Bowie and Laurel Smith-Doerr. 2002. "The Spatial Clustering of Science and Capital: Accounting for Biotech Firm-Venture Capital Relationships." *Regional Studies* 36(3):291-305. doi: 10.1080/00343400220122089.

Powers, Pike. 2004. "Building the Austin Technology Cluster: The Role of Government and Community Collaboration in the Human Capital." Pp. 53-71.

Rai, Arun and Xinlin Tang. 2014. "Research Commentary—Information Technology-Enabled Business Models: A Conceptual Framework and a Coevolution Perspective for Future Research." *Information Systems Research* 25(1):1-14. doi: 10.1287/isre.2013.0495.

Reynolds, Paul D. 1987. "New Firms: Societal Contribution Versus Survival Potential." *Journal of Business Venturing* 2(3):231-46.

Rogers, Everett M. 1995. *Diffusion of Innovations*. New York: Free Press.

Romanelli, Elaine and Maryann Feldman. 2004. "Anatomy of Cluster Development: Emergence and Convergence in the Us Human Biotherapeutics, 1976–2003." *In P. Braunersfjeld and M.P. Feldman (Eds.), The Genesis of Clusters: Technology-Based Industrial Development. New York: Oxford University Press*.

Rosenbaum, James E. 1979. "Tournament Mobility: Career Patterns in a Corporation." *Administrative Science Quarterly* 24(2):220.

Rosenberg, David. 2002. *Cloning Silicon Valley: The Next Generation High-Tech Hotspots*: Pearson Education.

Rosenfeld, Rachel A. 1992. "Job Mobility and Career Processes." *Annual Review of Sociology* 18(1):39-61. doi: 10.1146/annurev.so.18.080192.000351.

Ross, Peter K. and Michael Blumenstein. 2015. "Cloud Computing as a Facilitator of Sme Entrepreneurship." *Technology Analysis & Strategic Management* 27(1):87-101.

Rothwell, Jonathan, Jose Lobo, Deborah Strumsky and Mark Muro. 2013. "Patenting Prosperity: Invention and Economic Performance in the United States and Its Metropolitan Areas." *Metropolitan Policy Program at Brookings*:1-49.

Ruef, Martin, Howard E. Aldrich and Nancy M. Carter. 2003. "The Structure of Founding Teams: Homophily, Strong Ties, and Isolation among Us Entrepreneurs." *American sociological review*:195-222.

Rynes, S. L., T. L. Giluk and K. G. Brown. 2007. "The Very Separate Worlds of Academic and Practitioner Periodicals in Human Resource Management: Implications for Evidence-Based Management." *Academy of Management Journal* 50(5):987-1008. doi: Doi 10.5465/Amj.2007.27151939.

Samila, Sampsa and Olav Sorenson. 2011. "Venture Capital, Entrepreneurship, and Economic Growth." *The Review of Economics and Statistics* 93(1):338-49.

Saxenian, AnnaLee. 1994. *Regional Advantage: Culture and Competition in Silicon Valley and Route 128*. Cambridge, Mass.: Harvard University Press.

Saxenian, AnnaLee. 1999. *Silicon Valley's New Immigrant Entrepreneurs*. San Francisco: Public Policy Institute of California.

Scherer, Stefani. 2001. "Early Career Patterns: A Comparison of Great Britain and West Germany." *European Sociological Review* 17(2):119-44. doi: 10.1093/esr/17.2.119.

Schumpeter, Joseph A. and Redvers Opie. 1934. *The Theory of Economic Development; an Inquiry into Profits, Capital, Credit, Interest, and the Business Cycle*. Cambridge, Mass.,: Harvard University Press.

Schumpeter, Joseph A. 1942. *Capitalism, Socialism, and Democracy*. New York, London,: Harper & Brothers.

Scott, W. Richard. 2014. *Institutions and Organizations: Ideas, Interests and Identities*, Vol. Fourth. Thousand Oaks, California: SAGE Publications, Inc.

Selingo, Jeffrey. 2017. "Six Myths About Choosing a College Major." in *The New York Times*.

Shah, Priti Pradhan, John P. Bechara, Joseph Kolars, Monica Drefahl, Nicholas LaRusso, Douglas Wood and Barbara Spurrier. 2014. "Temporal Elements in Career Selection Decisions: An Archival Study Investigating Career Decisions in Medicine." *Organization Science* 25(1):245-61. doi: 10.1287/orsc.2013.0838.

Shane, Scott and Daniel Cable. 2002. "Network Ties, Reputation, and the Financing of New Ventures." *Management Science* 48(3):364-81.

Shane, Scott and Toby Stuart. 2002. "Organizational Endowments and the Performance of University Start-Ups." *Management Science* 48(1):154-70.

Shane, Scott and Karl Ulrich. 2004. "50th Anniversary Article: Technological Innovation, Product Development, and Entrepreneurship in Management Science." *Management Science* 50(2):133-44. doi: 10.1287/mnsc.1040.0204.

Sichelman, Ted. 2015. "Startups & the Patent System: A Narrative." *LAW & SOCIETY PERSPECTIVES IN INTELLECTUAL PROPERTY, Deborah Halbert & William Gallagher, eds*:1-20.

Singh, Jasjit. 2005. "Collaborative Networks as Determinants of Knowledge Diffusion Patterns." *Management Science* 51(5):756-70. doi: 10.1287/mnsc.1040.0349.

Singh, Param Vir, Yong Tan and Vijay Mookerjee. 2011. "Network Effects: The Influence of Structural Capital on Open Source Project Success." *MIS Quarterly* 34(4):813-29.

Singh, Param Vir and Corey Phelps. 2013. "Networks, Social Influence, and the Choice among Competing Innovations: Insights from Open Source Software Licenses." *Information Systems Research* 24(3):539-60. doi: 10.1287/isre.1120.0449.

Sjaastad, Larry A. 1962. "The Costs and Returns of Human Migration." *The Journal of Political Economy*:80-93.

Smilor, R. W., D. V. Gibson and G. Kozmetsky. 1989. "Creating the Technopolis: High Technology Development in Austin, Texas." *Journal of Business Venturing*:49-67.

Sorenson, O. and P. G. Audia. 2000. "The Social Structure of Entrepreneurial Activity: Geographic Concentration of Footwear Production in the United States, 1940–1989." *American Journal of Sociology* 106(2):424-61. doi: Doi 10.1086/316962.

Sorenson, Olav and Toby E. Stuart. 2001. "Syndication Networks and the Spatial Distribution of Venture Capital Investments." *American Journal of Sociology* 106(6):1546-88.

Sorenson, Olav. 2003. "Social Networks and Industrial Geography." *Journal of evolutionary economics* 13(5):513-27. doi: 10.1007/s00191-003-0165-9.

Sorenson, Olav and David M. Waguespack. 2006. "Social Structure and Exchange: Self-Confirming Dynamics in Hollywood." *Administrative Science Quarterly* 51(4):560-89.

Sorenson, Olav and Michelle Rogan. 2014. "(When) Do Organizations Have Social Capital?*." *Annual Review of Sociology* 40(1):261-80. doi: 10.1146/annurev-soc-071913-043222.

Stam, Wouter, Souren Arzlanian and Tom Elfring. 2014. "Social Capital of Entrepreneurs and Small Firm Performance: A Meta-Analysis of Contextual and Methodological Moderators." *Journal of Business Venturing* 29(1):152-73. doi: 10.1016/j.jbusvent.2013.01.002.

Steiner, Michael. 1998. "The Discreet Charm of Clusters: An Introduction." *Clusters and regional specialisation*:1-17.

Stenard, Briana Sell and Henry Sauermann. 2016. "Educational Mismatch, Work Outcomes, and Entry into Entrepreneurship." *Organization Science* 27(4):801-24. doi: 10.1287/orsc.2016.1071.

Stewman, S. and S. L. Konda. 1983. "Careers and Organizational Labor Markets: Demographic Models of Organizational Behavior." *American Journal of Sociology* 88(4):637-85. doi: Doi 10.1086/227728.

Stringer, Scott M. 2012. "Start-up City: Growing New York City's Entrepreneurial Ecosystem for All." Vol.: A Report of the Manhattan Borough.

Strumsky, Deborah. 2014, "Strumsky Granted Patent and Patent Application Database". (https://clas-pages.uncc.edu/innovation/granted-patents/).

Stuart, Toby and Olav Sorenson. 2003. "The Geography of Opportunity: Spatial Heterogeneity in Founding Rates and the Performance of Biotechnology Firms." *Research Policy* 32(2):229-53.

Summit, Bloomberg Technology. 2013. (https://events.bloomberglive.com/events/tech-2013/).

Susarla, Anjana, Jeong-Ha Oh and Yong Tan. 2016. "Influentials, Imitables, or Susceptibles? Virality and Word-of-Mouth Conversations in Online Social Networks." *Journal of Management Information Systems* 33(1):139-70. doi: 10.1080/07421222.2016.1172454.

Tambe, Prasanna and Lorin M. Hitt. 2013. "Job Hopping, Information Technology Spillovers, and Productivity Growth." *Management Science* 60(2):338-55. doi: 10.1287/mnsc.2013.1764.

Tieger, Paul D., Barbara Barron and Kelly Tieger. 2014. *Do What You Are: Discover the Perfect Career for You through the Secrets of Personality Type*: Little, Brown.

Todaro, Michael P. 1969. "A Model of Labor Migration and Urban Unemployment in Less Developed Countries." *The American Economic Review*:138-48.

Totterman, H. and J. Sten. 2005. "Start-Ups: Business Incubation and Social Capital." *International Small Business Journal* 23(5):487-511. doi: 10.1177/0266242605055909.

Tsai, Wenpin and Sumantra Ghoshal. 1998. "Social Capital and Value Creation: The Role of Intrafirm Networks." *The Academy of Management Journal* 41(4):464-76. doi: 10.2307/257085.

Uzzi, Brian. 1997. "Social Structure and Competition in Interfirm Networks: The Paradox of Embeddedness." *Administrative Science Quarterly* 42(1):35-67.

Valley, Joint Venture Silicon. 2016. "Silicon Valley Index." Vol.: Institute for Regional Studies.

Van den Bulte, Christophe and Rudy K. Moenaert. 1998. "The Effects of R&D Team Co-Location on Communication Patterns among R&D, Marketing, and Manufacturing." *Management Science* 44(11-part-2):S1-S18. doi: 10.1287/mnsc.44.11.S1.

Venkataraman, S. and A. H. Van de Ven. 1998. "Hostile Environmental Jolts, Transaction Set, and New Business." *Journal of Business Venturing* 13(3):231-55. doi: Doi 10.1016/S0883-9026(97)00051-7.

Venkataraman, Sankaran. 2004. "Regional Transformation through Technological Entrepreneurship." *Journal of Business Venturing* 19(1):153-67. doi: 10.1016/j.jbusvent.2003.04.001.

Vissa, Balagopal and Aya S. Chacar. 2009. "Leveraging Ties: The Contingent Value of Entrepreneurial Teams' External Advice Networks on Indian Software Venture Performance." *Strategic Management Journal* 30(11):1179-91. doi: 10.1002/smj.785.

Vissa, Balagopal. 2012. "Agency in Action: Entrepreneurs' Networking Style and Initiation of Economic Exchange." *Organization Science* 23(2):492-510. doi: 10.1287/orsc.1100.0567.

Vroom, V. H. and K. R. Maccrimmon. 1968. "Toward a Stochastic Model of Managerial Careers." *Administrative Science Quarterly* 13(1):26-46. doi: Doi 10.2307/2391260.

Wagner, Joachim. 2003. "Testing Lazear's Jack-of-All-Trades View of Entrepreneurship with German Micro Data." *Applied Economics Letters* 10(11):687-89.

Webber, Douglas A. 2016. "Are College Costs Worth It? How Ability, Major, and Debt Affect the Returns to Schooling." *Economics of Education Review* 53:296-310. doi: 10.1016/j.econedurev.2016.04.007.

Westlund, Hans and Roger Bolton. 2003. "Local Social Capital and Entrepreneurship." *Small Business Economics* 21(2):77-113.

White, Harrison C. 1970. *Chains of Opportunity: System Models of Mobility in Organizations*. Cambridge, Mass: Harvard University Press.

White, R. J. and A. E. Green. 2010. "Opening up or Closing Down Opportunities?: The Role of Social Networks and Attachment to Place in Informing Young Peoples' Attitudes and Access to Training and Employment." *Urban Studies* 48(1):41-60. doi: 10.1177/0042098009360234.

Williams, C. L., C. Muller and K. Kilanski. 2012. "Gendered Organizations in the New Economy." *Gend Soc* 26(4):549-73. doi: 10.1177/0891243212445466.

Wonglimpiyarat, Jarunee. 2006. "The Dynamic Economic Engine at Silicon Valley and Us Government Programmes in Financing Innovations." *Technovation* 26(9):1081-89. doi: 10.1016/j.technovation.2005.09.005.

Woodward, Douglas, Octavio Figueiredo and Paulo Guimaraes. 2006. "Beyond the Silicon Valley: University R&D and High-Technology Location." *Journal of Urban Economics* 60(1):15-32.